

European firms, Panic Borrowing and Credit Lines Drawdowns: What did we learn from the COVID-19 Shock?

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Abstract

We show that European firms, at the peak of the COVID-19 shock in 2020:Q2, went into a "panic borrowing" status and drew down €87bn in a very short period. We show that firms with less stringent solvency and liquidity constraints drew down their credit lines and accumulated cash. Our study exploits the implications of the social distancing policies to corporate operations across Europe and proposes a novel empirical framework that identifies panic borrowing while accounting for the endogeneity between credit line drawdowns and an underlying borrowing ability during the COVID-19 shock. We use COVID-19 infection data and proxies for social distancing policies in Europe to study if the increase in risk following the COVID-19 shock can explain the panic borrowing while accounting for possible endogenous credit lines drawdowns. Finally, we show that European corporate drawdowns during the pandemic crisis increased drawdowns, on average, by 3.35 percentage points in response to an unexpected one percentage point fall in their cash flows but only when firms' earnings are negative. This result is driven by the lockdown policies introduced in Europe.

Keywords: Corporate credit lines, cash holding, investment, default risk

Classification codes: G21, G32, G33

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1 Introduction

Over the past decade, credit lines have channelled a significant amount of credit from banks to European enterprises. For example, we estimate that European firms (in this paper we focus on firms within the euro area) drew down about €87bn, in a short time, during the pandemic crisis to stay afloat. It was an unprecedented fly to liquidity on a macroeconomic scale during which the average credit line to total assets ratios rose from 4.72% in 2020:Q1 to 5.15% in 2020:Q2 (average of 7.00% during 2020:Q2-Q3). Recently [Acharya et al. \(2020\)](#) showed similar results for US firms. Why did European firms draw down their credit lines at the start of the pandemic shock, that is, in 2020:Q2? Theoretical models would predict that firms draw down their credit lines to support investments as an alternative to cash financing. Do we find similar evidence for European firms in 2020Q2? More important, which firms drew down credit lines, and accumulated cash? Answering these questions is very important not just from a policy perspective but also for corporate liquidity management. For example, theoretical models do not consider using credit lines for cash accumulation (what we call panic borrowing in this paper) and, consequently, a possible endogenous role of credit line drawdowns in firms' decisions. We contribute empirically to shed lights on this issue in several ways by using COVID-19 data and proxies for mobility across Europe and employing quasi-natural experiments.

The COVID-19 shock led to a policy response across Europe which was not uniform (we call it country flexibility). Social distancing policies introduced by European countries were very different in different countries. Did social distancing policies contribute to the "panic borrowing"? We are not aware of other studies investigating such important issues. We employ infection rates in Europe and a proxy for social distancing policy in a given country (Oxford Stringency Index). We show that country flexibility is important as firms in countries where COVID-19 infection rates were higher and social distancing policies stricter, went into a "panic borrowing" and drew down their credit lines. We also extend our study to consider work flexibility and credit line drawdowns. [Campello et al. \(2020\)](#) show for the US that work flexibility is important to understand job hiring in the US during the COVID-19 period. We extend this to the European market and firms' liquidity risk management during the COVID-19 shock. We show that work flexibility is also important to understand firms' behaviour, that is, the "panic borrowing". Finally, we show that the "panic borrowing" amongst European firms and work flexibility are unique to the COVID-19 crisis and do not extend to either the 2008 financial crisis or the 2012 European crisis. The panic borrowing observed in Europe seems unique to the COVID-19 crisis as this was mainly driven by the social distancing policies introduced in Europe. These are new and important results as they suggest that the nature of the shock (COVID-19 shock vs financial crisis shock) does matter to understand why European firms draw down credit lines and accumulate cash. Finally, our results suggest a novel interplay between social distancing rules, a fall in revenues, and credit lines drawdown for precautionary reasons. This new mechanism also has important implications for banks when granting credit to firms and introduces a new source of risk for banks (social distancing policies or work flexibility) associated with firms' idiosyncratic risk.

The results discussed in the first part of the paper are consistent with the ones for US firms as discussed in [Acharya et al. \(2020\)](#), suggesting a higher degree of international corporate market integration. However, given that the dash for cash in this paper and related study for US market, point towards an endogenous role for credit lines in corporate liquidity management, we also employ

robust econometric settings and real COVID-19 infection rates to tackle this issue. In sum, the results discussed in the first part of our paper, complement and extend [Acharya et al. \(2012\)](#), [Campello et al. \(2011\)](#), and [Acharya et al. \(2020\)](#).

Credit lines are financial contracts enabling firms to draw funds from their bank accounts and have financing available as contingent liquidity provisions to offset shocks. Hence, credit lines are contingent liquidity lines which can be viewed as insurance against unexpected future liquidity requirements. This funding vehicle is crucial in Europe given the high reliance of European firms on bank-based financing, further underscoring its significance relative to alternative capital market-based financings in the US. Furthermore, our study on European firms complements others (for example, [Acharya et al. \(2020\)](#)) and allows us to study international financial and corporate markets integrations as pointed out in [Berg et al. \(2017\)](#).

Figure (1) shows the total amount (in billions of euros) of credit lines drawdowns by European firms, across different sectors, in 2020:Q2. Contrary to alternative reports, we estimate that a total of €87bn were taken out of credit lines between 2020:Q1 and 2020:Q2 and the largest part, €49bn, was taken out of credit lines in 2020:Q2 alone. Figure (1) shows that industrials and materials were the sectors that relied significantly on credit lines in 2020:Q2 in terms of the total credit value, whilst energy, real estate and materials are amongst the top three sectors using credit lines to finance operations. The lower panel shows quarterly changes where energy, utilities and materials have further increased their reliance on credit lines. In contrast, energy, technology and materials have marginally increased their drawdown to total assets ratios during 2020:Q2 relative to the previous quarter.

[Sufi \(2009\)](#) studies the substitution effect between internal (cash/cash holdings) and external (credit lines) fundings using data when credit was abundant and shows that firms using credit lines are generally profitable firms. [Campello et al. \(2011\)](#), using data for the 2008 financial crisis and US firms confirms a substitution effect between cash holding and credit lines when firms face a severe credit shortage. We extend and complement these studies by studying European firms during the COVID-19 shock with the main focus on external borrowing via credit lines as this part of the literature is more limited and, critically, studying why firms draw down their credit lines to accumulate cash.

If we consider the COVID-19 shock, while [Li et al. \(2020\)](#) and [Greenwald et al. \(2021\)](#), for the US market, show that firms use credit lines to support investments, [Bosshardt & Kakhbod \(2020\)](#), and [Acharya et al. \(2020\)](#), again for the US market, show that firms use instead credit lines for precautionary reasons. We also contribute to this recent literature by studying firms' financing behaviour in the presence of solvency and liquidity constraints during the COVID-19 period. We show that European firms do not use credit lines to support investment during the COVID-19 shock, but accumulate cash.

[Acharya et al. \(2012\)](#) show that the literature investigating the precautionary motive for holding cash may have produced misleading results due to the endogeneity of cash holdings and credit risk. They show that high credit rating firms behave similarly to more financially constrained firms (lower credit quality firms) in holding cash. We speak to this literature as we explicitly consider solvency and liquidity constraints for European firms during the COVID-19 shock. We also empirically extend it by considering endogeneity between credit risk and cash accumulation as discussed in [Acharya et al. \(2012\)](#), but also between credit risk and credit lines drawdowns and employing quasi

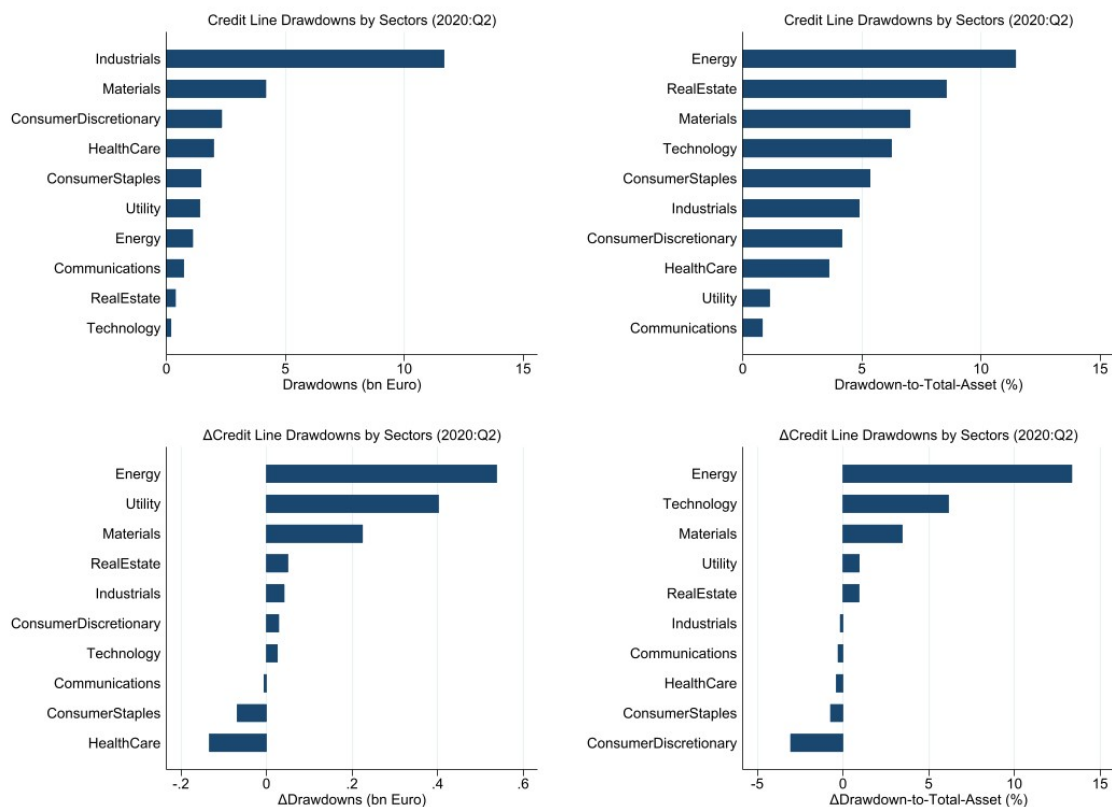


Figure 1. The top left diagram shows credit line drawdowns in different sectors during the second quarter of 2020, followed by similar quarterly changes between 2020:Q1-Q2. The diagram on the bottom-left shows the changes in credit line drawdowns in 2020:Q2, compared with the previous quarter. The horizontal axis shows the changes in the number of drawdowns in billion euros. The vertical axis shows different sectors. The diagram on the right shows the changes in drawdown size in 2020:Q2, compared with the previous quarter. The horizontal axis shows the changes in the drawdown to total assets in percentage. The vertical axis shows different sectors. The sectors Energy, Materials and Utilities increased their drawdown levels in a significant way during the shock, which suggests that firms in these sectors are those more exposed to the COVID-19 shock and topped up cash through credit line drawdowns.

natural experiments to address it.

Papanikolaou & Schmidt (2022) find that the COVID-19 shutdown had a heterogeneous effect across firms due to the degree of opportunity to work from home (work flexibility). They find that firms with fewer opportunities to work from home performed worse, as measured by a fall in expected revenue and credit quality deterioration. Following Campello et al. (2011, 2020), we extend this setting and employ infection rates as well as proxy for social distancing policies in Europe, and show that firms hit by the COVID-19 shock saw their expected revenues, as measured by EBITDA, fall. They increased credit line drawdowns and cash holdings. We show that work flexibility was the trigger for this unexpected shock and the following "panic borrowing".

2 Data

We collect credit lines data from Bloomberg and, unless mentioned, use all the firms with available information between 2018:Q4 and 2020:Q3. We exclude financial companies, including banks, investment and insurance companies, private equity companies, security and commodity exchange and wealth management companies and focus on firms within the Euro area where there are 324 non-financial firms in total between 2018:Q4 to 2020:Q3.

We use credit line drawdown and the total amount of committed credit lines. Specifically, the total credit line refers to the total amount of committed lines of credit that firms can access. The available credit line is the remaining amount that a bank (financial institution) has agreed to lend and is equivalent to the undrawn amount of the credit line. The drawdown share of the credit lines is calculated as the total credit line minus the undrawn credit line. We supplement credit line data by including firms' financial variables from Bloomberg. The industry classification used in this paper is based on the Bloomberg Industry Classification System (BICS).¹

Table (1) shows the summary statistics between 2018:Q4-2020:Q3 with 1,157 credit facility observations. The credit line usage and the undrawn rates are 19.1 and 80.9 per cent, respectively.² The drawdown size, drawdown-to-non-cash assets ratio, is about 5 per cent and the undrawn size, undrawn amount of credit line scaled by non-cash assets, is about 12 per cent.

Following Sufi (2009), we use non-cash assets as a scale instead of total assets to mitigate the potential influence of cash holdings on drawdowns. We adjust some financial variables by non-cash assets, the total assets excluding cash and cash equivalent. Accordingly, *Cash Holdings* represents the cash and cash equivalent scaled by non-cash assets. *Cash Flow*, *CAPEX*, and *Tangible Assets* are cash flow, capital expenditure and tangible assets scaled by non-cash assets separately. $\text{Log}(\text{assets})$ is the natural logarithm of non-cash assets.

| Variable | N | Mean | S.D. | Min | 0.25 | Median | 0.75 | Max |
|-------------------|-------|--------|--------|--------|--------|--------|--------|--------|
| Cash Holdings | 1,157 | 0.107 | 0.116 | 0.000 | 0.041 | 0.076 | 0.142 | 1.949 |
| CAPEX | 969 | 0.012 | 0.012 | 0.000 | 0.004 | 0.009 | 0.016 | 0.175 |
| Credit Line Usage | 827 | 0.191 | 0.277 | 0.000 | 0.000 | 0.000 | 0.350 | 1.000 |
| Drawdown Size | 842 | 0.051 | 0.108 | 0.000 | 0.000 | 0.000 | 0.041 | 0.758 |
| Cash Flow | 1,055 | 0.028 | 0.031 | -0.372 | 0.016 | 0.027 | 0.040 | 0.268 |
| Undrawn Size | 1,133 | 0.117 | 0.108 | 0.000 | 0.046 | 0.090 | 0.148 | 0.923 |
| Undrawn Capacity | 827 | 0.809 | 0.277 | 0.000 | 0.650 | 1.000 | 1.000 | 1.000 |
| P/B Ratio | 1,130 | 3.731 | 45.989 | 0.014 | 1.062 | 1.683 | 2.745 | 1,545 |
| Log(assets) | 1,157 | 21.420 | 2.075 | 15.531 | 19.915 | 21.558 | 22.783 | 26.859 |
| Tangible Assets | 1,144 | 0.838 | 0.272 | 0.001 | 0.659 | 0.887 | 1.013 | 2.938 |
| Leverage | 1,157 | 0.302 | 0.169 | 0.000 | 0.190 | 0.283 | 0.403 | 1.203 |

Table 1. Summary Statistics

Revolving credit lines are facilities commonly used by banks to supply cash to firms. Figure (2) shows the weighted credit line drawdowns and credit lines drawdown size for all Euro-area firms in the sample. In the left-hand-side panel, we scale drawdowns by the number of firms in each quarter.³ European firms drew down credit lines at the start of the pandemic and in the following months.

We also note a significant increase in cash holdings during the same period. The increase in cash holdings could be associated with investments. Figure (3A) shows the trend in liquidity accumulation before and after the pandemic period. Specifically, average cash holdings, including cash and cash-equivalent components, scaled by non-cash assets, increased sharply during the pandemic. The sharp increase in cash holdings is consistent with (Anderson & Carverhill (2012),

¹Standard Industry Classification (SIC) and NAICS codes are only sparsely reported by Bloomberg. Thus we use the industry classification code reported by Bloomberg.

²Credit line usage is measured by the ratio of drawn-down to the total amount. The undrawn rate is equal to one minus credit line usage.

³For example, 286 firms had, in total, 279.465b euros in committed credit lines at the end of 2018:Q4, and the average committed amount is $\text{€}279.465\text{b} / 286 = \text{€}0.977\text{b}$. In 2019:Q1, only 80 firms showed a total of 63.689b euros in the committed credit line, with the average being $63.689\text{b} / 80 = 0.796\text{b}$ euros.

Bolton et al. (2011)) and suggests an increase in liquid assets, probably to mitigate the impact of a possible liquidity shocks. In a nutshell, EU firms may have taken out of their credit lines in anticipation of a possible liquidity shock. However, credit line drawdowns can also be associated with investments. In Figure (3B), we use capital expenditure as a proxy for investment. There is limited evidence that EU firms used credit lines to support investments during the pandemic. Acharya & Steffen (2020b) provide empirical evidence for the United States and show that the “dash for cash” of US firms during the pandemic period was mainly driven by precautionary saving reasons, although they do not study firms’ investment under the COVID-19 period. Bosshardt & Kakhbod (2020) show similar evidence. In Table A1 in the Appendix, we support these findings by using a panel regression and capital expenditure as a dependent variable. We do not find evidence that firms used credit lines to support investments in 2020Q2.

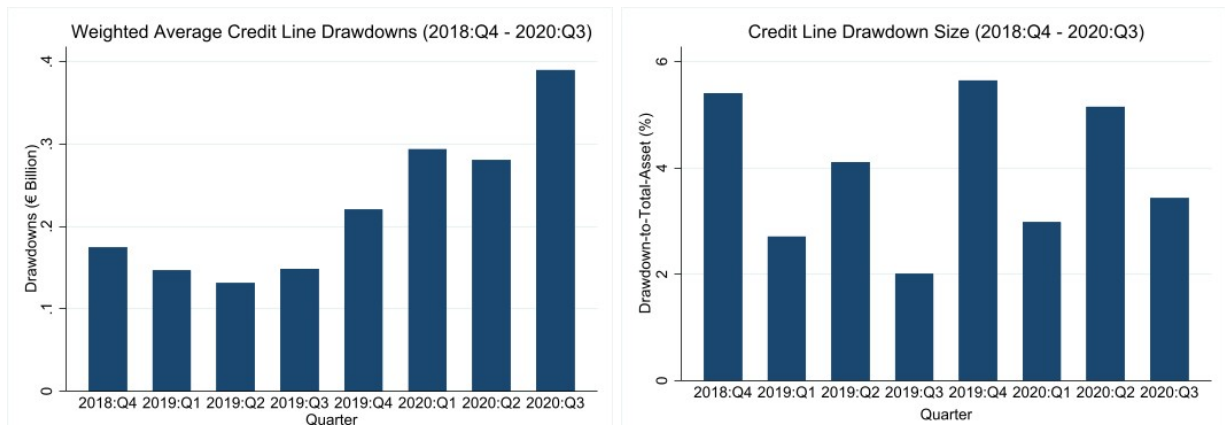


Figure 2. The left diagram reports the average credit line drawdowns in the firm level during 2018:Q4 - 2020:Q3. The right diagram reports the drawdowns scaled by total assets during the same period.

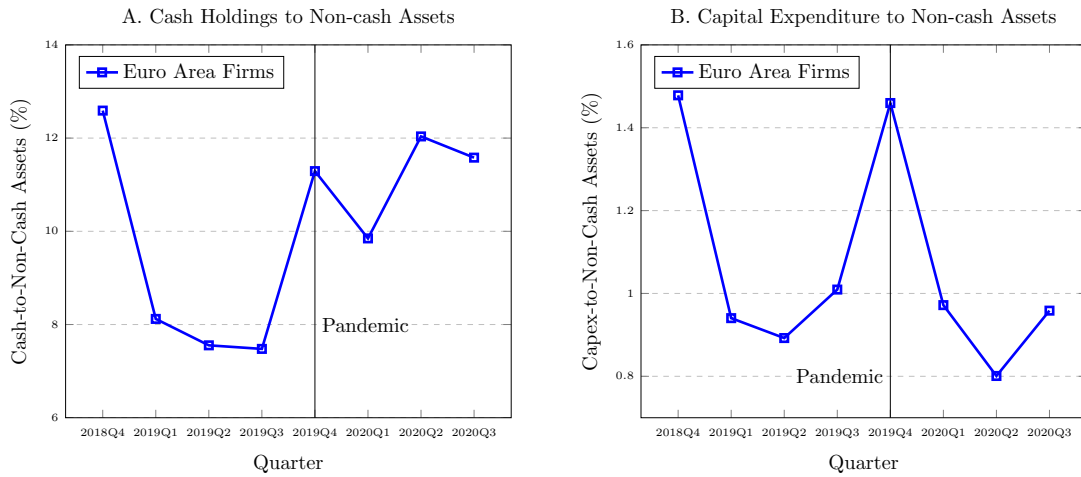


Figure 3. Cash Holdings and Capital Expenditure

3 Financial Constraints

Sufi (2009) shows that, in general, less financially constrained firms rely on credit lines while financially constrained firms use cash. Sufi’s study considers a period when credit was abundant, which may have driven the empirical results. Campello et al. (2011) study the financial crisis period. They show that firms substitute between internal (cash holding) and external liquidity

(credit lines) in the presence of liquidity shocks. However, the main focus of that study is on firms' real side (investment) decisions and credit lines. [Acharya & Steffen \(2020b\)](#) study the recent COVID-19 period and how firms raise cash to offset changes in credit risk following the COVID-19 shock. They show that credit risk is important to understand how US firms raised cash during the pandemic and why they dashed for cash. Our paper builds and complements [Acharya & Steffen \(2020b\)](#) in several different ways. Firstly, for European firms, we study the mechanism triggering the dash for cash (we call it panic borrowing). Secondly, we consider other important constraints: country and work flexibility. Thirdly, we allow for an endogenous role of credit lines. That is, we conjecture that credit line decisions made by firms at the peak of the pandemic crisis and cash holdings were driven by the unprecedented shock (which increased risk) following the higher number of COVID-19 infections. Our paper considers these additional constraints and shows some novel results for European firms.

The paper proceeds as follows. In the first part, we investigate why firms raised cash during the pandemic period. In so doing, we contribute to an important strand of literature studying firms' financial constraints and liquidity accumulation. More importantly, we extend it to study the relationship between firms' financial constraints and credit line drawdowns (external financing) ([Acharya et al. 2012](#)), as this literature is somehow more limited.

In the second part of the paper, we study if social distancing rules in Europe (country flexibility) and within industries (work flexibility) help to understand why firms drew down credit lines to accumulate cash. The capacity of a firm to access external financing is heterogeneous across firms, depending, amongst other things, on their underlying current and future capacity to meet liabilities. Unexpected shocks, such as the lockdown during the pandemic period, can produce undesirable outcomes, particularly for the firms affected by social distancing policies. For example, more stringent social distance policies in a given country (less country flexibility) may impact firms' expected cash flow, leading firms to draw down their credit lines and increase cash holdings. ([Almeida et al. 2004](#), [Bates et al. 2009](#)). [Acharya et al. \(2012\)](#) show that even firms with lower credit risk in the presence of financial constraints behave similarly to firms with higher credit risk. We find some evidence of this for European firms. In the next section, we shall consider credit risk (firms' solvency) ([Acharya et al. 2012](#)).

3.1 Solvency-Driven Credit Line Draw downs

In this section, we empirically study how solvency risk drives firms' decisions to draw down credit lines, focusing on the substitution effect between internal resources (cash holdings) and external ones (credit lines) in the presence of solvency constraints. We study the COVID-19 period and European firms. In general, constrained firms tend to hold more cash for investment than unconstrained ones ([Denis & Sibilkov 2010](#), [Farre-Mensa & Ljungqvist 2016](#)). [Acharya et al. \(2012\)](#), for US, show that financially constrained firms accumulate more cash for precautionary reasons and that higher cash accumulation, in general, is associated with high credit risk. They show that in the presence of financial constraints (for example, a significant fall in revenue affecting firms' credit risk profile), high cash holdings firms behave the same way as low cash holding firms. More recently, [Acharya & Steffen \(2020a\)](#) show evidence in support of this for US firms at the start of the COVID-19 period. They also show that financially constrained firms (BBB and Non-IG) drew down their credit lines at an increased speed and accumulated cash at the start of the pandemic crisis. However, only

firms whose credit risk profile was quickly deteriorating continued to access credit lines in the second part. In this section, we build on this literature (Whited & Wu 2006, Almeida & Campello 2007, Farre-Mensa & Ljungqvist 2016) and empirically study the relationship between credit line drawdowns (cash holdings) and solvency risk across different firms during the COVID-19 shock.

Table (2) shows an example of a corporate balance sheet. The left-hand side shows total assets and contains cash, cash equivalent and risky investment.⁴ The right-hand side shows the liabilities and shareholders' equity, consisting of (total) debt and equity. The total amount on the left-hand side should equal that of the right-hand side. We assume that the firm has to cover its cost of debt using all the returns on total assets when facing a financial or pandemic crisis. The total amount on the left-hand side, return on cash and cash equivalent plus return on a risky investment, and the one on the right-hand side, cost of debts, are also balanced.

| Assets | Liabilities |
|---------------------------|--------------------|
| Cash & Cash Equivalent | Debts |
| Risky Investments | |
| | Equity |

Table 2. Balance Sheet

Assume that A is the total assets, C cash and cash equivalent, I risky investment, D is the total debt, and E is the shareholders' equity. Also, we let R_C , R_I , R_D be the interest rates on cash and cash equivalent, risky investment, and debt, respectively. Based on table (2), total assets, cash and cash equivalent, risky investment, debt, and equity should simultaneously satisfy the balance sheet equation below:

$$C + I = D + E$$

To study firm's behaviour in response to solvency risk following an unexpected shock to the risky investment, we consider the following solvency condition showing an end of period assets value equal to the total debt obligations plus interests:

$$R_C \cdot C + R_I \cdot I = R_D \cdot D$$

The solvency condition assumes that firms remain just-solvent while the shareholder value is zero as a result of underperformance of the risky investments. Rearranging the above equations by substituting I and D , we have

$$R_I = \frac{R_D \cdot (A - E) - R_C \cdot C}{A - C}$$

Suppose that the cost of debt, R_D , is equal to the return on cash and cash equivalent, R_C . Since firms seek to make the rate of return on cash or short-term investment at least equal to the interest rate of liability, we can rewrite this expression as:

$$\frac{R_I}{R_D} = 1 - \frac{E}{A - C} \tag{1}$$

⁴Risky investment contains long-term investment and fixed assets, equal to total assets minus cash and cash equivalent, namely, non-cash assets. This type of asset is far less liquid than cash. Investors or firms cannot convert them immediately when facing a liquidity shortfall.

The left-hand side shows the profitability of risky investments, or non-cash assets, to hedge the interest rate of total debts. The right hand side is the relationship between equity E and risky investment ($A - C$). In other words, it shows that profitability is determined by the proportion of equity value to risky investment. We name the ratio R_I/R_D the risky-investment-to-debt ratio (RID). For example, assume that the rate of debt is 5%. If RID is 0.9, it means that the rate of return on all the risky investments should be at least 4.5% ($5\% \times 0.9$) to hedge the debts. If RID falls, less return on risky investment is needed to compensate for debt. Therefore, a fall of the RID means that less risky investment is needed to maintain the debt coverage, given constant equity.

To study the association between solvency ratio (RID) and credit line drawdowns, we use two approaches. First, we use the drawdown amount of credit lines scaled by non-cash assets, namely, the drawdown size. Subsequently we also use credit line usage. We employ the following model:

$$\begin{aligned} Drawdown_{i,t} = & \alpha + \beta_1 RID_{i,t-1} + \beta_2 (RID_{i,t-1} \times 2020:Q2) \\ & + \gamma X_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (2)$$

where $Drawdown_{i,t}$ is (i) drawdown size and (ii) credit line usage. $RID_{i,t-1}$ is a variable indicating risky-investment-to-debt ratio:

$$RID = 1 - \frac{Book\ Value}{Total\ Assets - Cash\ \&\ Cash\ Equivalent} \quad (3)$$

$2020:Q2$ is a dummy equal to 1 proxying the liquidity shock induced by COVID-19. $X_{i,t-1}$ controls, consisting of the logarithm of non-cash assets, the undrawn credit lines scaled by non-cash assets, the price-to-book ratio, the tangible assets related to non-cash assets, and the leverage ratio.

Table (3) shows the results. Columns 1 to 4 in Table (3) show that the coefficient on RID, β_1 , is statistically significant and positive for the full sample. Higher insolvency risk is associated with higher credit lines drawdowns. However, there is a shift in the sign of the coefficient if we consider the interaction coefficient, $RID_{i,t-1} \times 2020:Q2$. Overall, columns 5 and 8 show similar results using credit line usage. The positive coefficient on RID shows that the higher the RID, the lower the solvency (i.e. the credit risk of the firm increases), and the higher the access to credit lines. On the other hand, the negative coefficient on the dummy in 2020:Q2 is interesting as it seems to suggest a negative association between credit line drawdowns and solvency risk.⁵ In a nutshell, lower-risk firms drew down credit lines in 2020:Q2.⁶ In Panel B of Table (3), we shed further lights on the previous results. We divide firms (in 2020:Q2) into three groups according to the RID: Low Risk (25%), Medium Risk (50%) and High Risk (25%).⁷

The coefficients in the three groups, for the full sample, are statistically insignificant, while they are significant in 2020:Q2 for the Low-Risk group. That is, lower-risk firms (in terms of solvency) drew down their credit lines in 2020:Q2. Figure (4) shows the change in credit lines between two quarters (for each of the three groups) between 2020:Q1 and 2020:Q2. Figure (4) projects the change in cash holding for the three groups. Low-risk firms are those with the greatest change in cash holding between 2020:Q1 and 2020:Q2. There is a negative association between credit line

⁵We also consider possible outliers and the significance increases from 10% to 5%. Results are available upon request

⁶In Appendix (C1), we also include cash holdings as a control variable and this is significant and carries a positive sign. Results are available in the online appendix

⁷We also considered alternative combinations, and results stay unchanged. Results are available upon request

drawdowns and solvency risk in 2020:Q2. In a nutshell, firms with a good solvency position drew down their credit lines during the COVID-19 shock and topped up their cash holding position.⁸ In the next section, we consider a liquidity measure.⁹

| | Drawdown Size | | | | Credit Line Usage | | | |
|-------------------------------|---------------------|----------------------|---------------------|--------------------|---------------------|--------------------|---------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Different Dummies | | | | | | | | |
| RID _{t-1} | 0.039*** (0.013) | 0.038*** (0.013) | 0.046*** (0.014) | 0.042** (0.017) | 0.119** (0.050) | 0.114** (0.050) | 0.147*** (0.052) | 0.101 (0.064) |
| RID _{t-1} × 2020:Q1 | | 0.031 (0.046) | | | | 0.139 (0.165) | | |
| RID _{t-1} × 2020:Q2 | | | -0.061* (0.032) | | | | -0.199* (0.109) | |
| RID _{t-1} × 2020:Q3 | | | | -0.007 (0.024) | | | | 0.040 (0.089) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 388 | 388 | 388 | 388 | 381 | 381 | 381 | 381 |
| Adjusted R ² | 0.059 | 0.057 | 0.066 | 0.057 | 0.057 | 0.056 | 0.063 | 0.055 |
| Panel B: Different Firm Types | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Risk | Medium Risk | High Risk | All Firms | Low Risk | Medium Risk | High Risk |
| RID _{t-1} | 0.046*** (0.014) | 0.018 (0.020) | -0.127 (0.085) | -0.090 (0.146) | 0.147*** (0.052) | 0.129 (0.112) | -0.242 (0.231) | 0.193 (0.499) |
| RID _{t-1} × 2020:Q2 | -0.061* (0.032) | -0.173*** (0.054) | 0.046 (0.174) | 0.092 (0.240) | -0.199* (0.109) | -0.556* (0.296) | 0.283 (0.478) | 0.284 (0.818) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 388 | 83 | 199 | 105 | 381 | 79 | 199 | 102 |
| Adjusted R ² | 0.066 | 0.127 | 0.019 | 0.189 | 0.063 | 0.017 | 0.085 | 0.241 |

Table 3. **RID Ratio and Drawdowns (Euro Area)** This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are credit lines usage. Panel A shows the baseline models given the interactions between the RID ratio and time dummies (2020:Q1-Q3), respectively. Panel B shows the baseline models for the whole sample (*All Firms*) and three subsamples (*Low-, Medium-, and High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

⁸We have also included Cash Holdings in Table (3) and the coefficients are significant but positive. Therefore, we exclude that a substitution effect between internal and external funding occurred in 2020Q2.

⁹Our analysis also considers an alternative specification where the firm indicators are constructed according to their ratios to total assets. The supplementary estimations reveal that the results remain robust to both specifications presented in Appendix (C1).

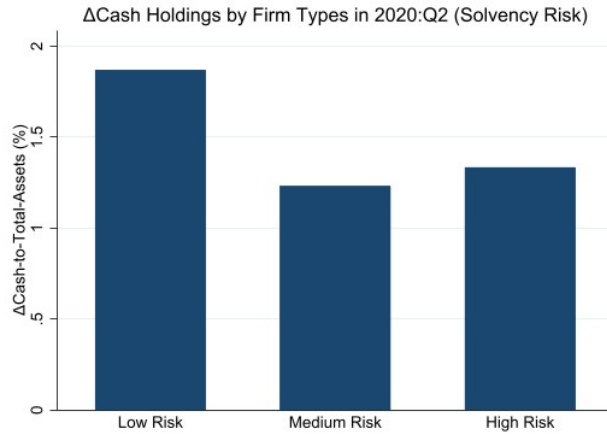


Figure 4. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current size less the previous one. The horizontal axis shows three types of firms: low-, medium- and high-risk ones. The vertical axis shows the changes in percentage.

3.2 Credit Ratings and Credit Lines Drawdowns

In Section ??, we showed that, over the whole sample, there is a positive and significant association between firms’ solvency risk and credit lines drawdowns, but this relationship changed in 2020:Q2. [Acharya & Steffen \(2020b\)](#) for the US market and the COVID-19 shock, show that firms drew down credit lines at the time of the COVID-19 shock, but the usage rate was higher among non-investment and BBB-rated firms. In the second period, BBB-rated firms still increased access to credit lines and topped up cash holdings. In this section, we replace our measure of firms’ solvency with credit ratings and consider changes in firms’ credit risk over three quarters (Q1-Q3), that is, before and after the COVID-19 shock (2020:Q2) and credit lines drawdowns.

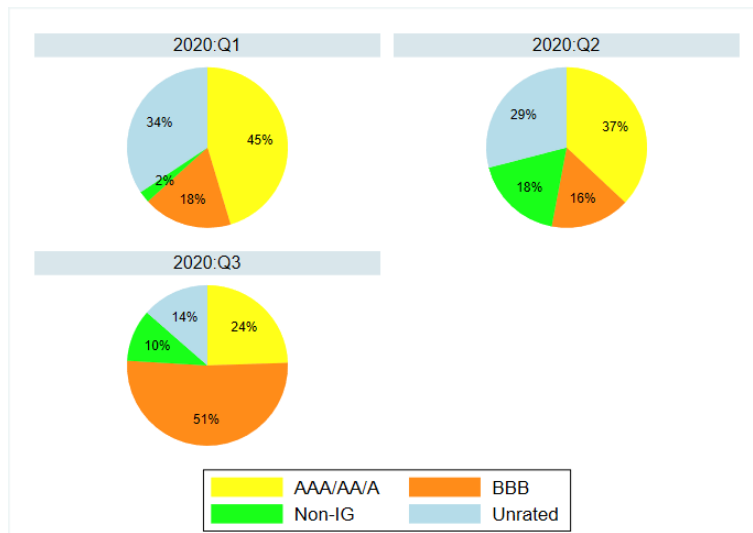


Figure 5. This diagram shows the distribution of credit line drawdowns across credit ratings during 2020:Q1 - Q3.

Figure (5) sheds further lights on the previous results. Firstly, while between 2020:Q1 and 2020:Q3, AAA-rated firms reduced their access to credit lines, BBB-rated firms increased it. This result is in line with [Acharya & Steffen \(2020b\)](#) for the US market. It suggests that the “Fallen Angels” phenomena (i.e. firms whose credit rating is quickly deteriorating due to COVID-19 shock) is not specific to the US but it extends to the European market, implying a more substantial degree of international corporate market integration. Overall, Figure (5) is consistent with our previous

results showing a negative association between firms’ solvency risk and credit lines drawdowns at the peak of the COVID-19 shock.

3.3 Liquidity Constraints and Credit Lines Drawdowns

We now turn to the relationship between firms’ liquidity constraints and credit line drawdown during the COVID-19 shock. Following the previous literature, amongst other things, we also contribute to the literature studying the substitution effect between internal and external cash, but with a focus on the COVID-19 period. Did firms with a good liquidity position draw down credit lines during the COVID-19 shock? And if so, why? For example, [Sufi \(2009\)](#) shows that profitable firms rely more on credit lines as high cash is critical to satisfying covenants. Sufi’s study focuses on a period when credit was abundant. [Berrospide & Meisenzahl \(2015\)](#) show that firms draw down credit lines to mitigate liquidity shocks, and [Ivashina & Scharfstein \(2010\)](#) show that firms, during the financial crisis, drew down their credit lines for precautionary reasons, while [Berrospide & Meisenzahl \(2015\)](#) show that firms drew down mainly to support investments. More recently, [Bosshardt & Kakhbod \(2020\)](#) show that US firms drew down their credit lines for precautionary reasons in anticipation of liquidity shock with heterogeneous variations across different sectors. We build and extend this literature by employing a new measure of liquidity constraint and shed new lights on firms’ decisions to draw down credit lines during the COVID-19 shock. We use firms’ drawdown size and credit line usage to represent firms’ financing decisions. More specifically, the drawdown size is the ratio of the credit line drawdowns scaled by non-cash assets. In contrast, credit line usage is a variable between 0 and 1, showing the drawdown amount in proportion to the total committed credit lines. We use the indicator developed by [Bosshardt & Kakhbod \(2020\)](#):

$$\text{Distress}_t = \frac{\text{Short-term Debt}_t - \text{Cash \& Cash Equivalent}_t - \text{Net Income}_t}{\text{Total Assets}_t} \quad (4)$$

where higher (lower) Distress_t implies a tighter (looser) liquidity-based financial constraint reflecting capacity to meet current liabilities. We apply this measure of firms’ distress to our firms before and after the start of the pandemic shock.

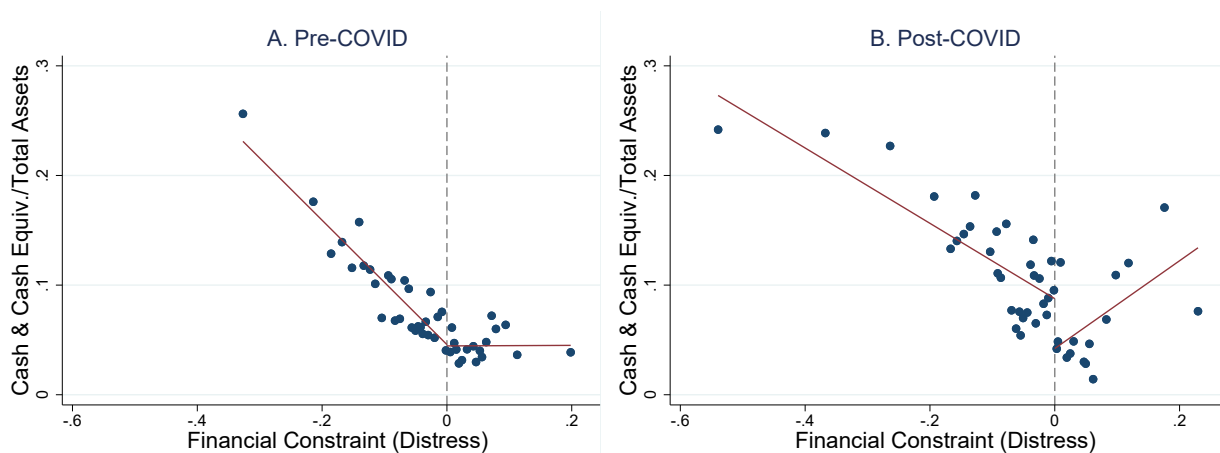


Figure 6. The diagram on the left-hand-side shows a regression-discontinuity design (RID) of cash and cash equivalents against financial constraint (distress) before COVID. The horizontal axis shows the distress ratio, and the vertical axis shows the cash and cash equivalents relative to total assets. The diagram on the right shows the RID after the pandemic outbreak. In addition, the horizontal axis presents the distress, and the vertical axis presents the cash and cash equivalents scaled by total assets.

Figure (6) shows the relationship between firms’ distress and cash and cash equivalent. We

consider two periods: before the COVID-19 period and after. We note that in the pre-COVID-19 period, only financially constrained firms held higher cash provisions, but that changed in the post-COVID-19 period when financially constrained and unconstrained firms held higher liquidity provisions. We test for the relationship between distress and credit line draw-downs by including quarter dummies and using the following specification:

$$Drawdown_{i,t} = \alpha + \beta_1 Distress_{i,t} + \beta_2 Distress_{i,t} \times 2020:Q2 + \gamma X_{i,t} + \epsilon_{i,t} \quad (5)$$

where the notations and controls are defined earlier.

Table (??) shows the results. We test the association between firms’ distress and credit line drawdowns using the whole sample and by conditioning on dummies that account for the pandemic shock in 2020:Q1, 2020:Q2 and 2020:Q3. Firstly, we note that only the intersection dummy in 2020:Q2 is statistically significant (Panel B). Secondly, we note a significant positive association between firms’ distress (cash holding) and credit line drawdowns in Panel B and the whole sample. [Campello et al. \(2011\)](#), for the financial crisis period and US firms, show a negative relationship between credit lines drawdowns and cash holdings and interpret it as a substitution effect between internal and external liquidity. We do not find this for European firms during the COVID-19 shock. We interpret the negative relationship between distress and credit line drawdowns as suggesting that firms with less stringent liquidity constraints used credit lines during the COVID-19 shock. In sum, firms with less stringent liquidity constraints drew down their credit lines and topped up cash holdings in 2020:Q2.

To shed further light on this result, we divide firms into three groups based on distress in Table (4). We use a 25%, 50% and 25% allocation as before. We have also used other combinations, and the results we present in this section remain robust. Results are available upon request¹⁰. There is a negative association between firms’ distress and credit line drawdowns in 2020:Q2. Firms with less stringent liquidity constraints drew down credit lines in 2020:Q2. This result contrasts with both [Campello et al. \(2011\)](#) and [Sufi \(2009\)](#).

In Figure (??), we show the change in cash holding in 2020:Q2 and Distress. Firms with the most remarkable change in cash holding were the ones within the Low Distress group. These results suggest that during the COVID-19 shock, firms with less stringent liquidity constraints drew-down credit lines and increased cash holdings. In the next section, we shall try to understand why. Firstly, we do not find a substitution effect as in [Campello et al. \(2011\)](#) for European firms during the COVID-19 shock, but instead, our results seem to suggest that in 2020:Q2 a “panic borrowing” took place amongst European firms which led to the observed fly to liquidity. These are new results, which we will investigate further in the next sections.

¹⁰In all these regressions, we have used the same controls as the ones in the previous sections.

| | Drawdown Size | | | Credit Line Usage | | |
|---------------------------------|---------------------|---------------------|----------------------|---------------------|--------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: 2020:Q1 | | | | | | |
| Distress _t | 0.095*** (0.025) | 0.082*** (0.022) | 0.097*** (0.025) | 0.200*** (0.070) | 0.143** (0.064) | 0.202*** (0.070) |
| Cash Holdings _t | 0.084 (0.057) | | 0.078 (0.057) | 0.333** (0.169) | | 0.327* (0.170) |
| Distress _t × 2020:Q1 | | -0.162 (0.138) | -0.144 (0.139) | | -0.234 (0.422) | -0.163 (0.423) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 804 | 804 | 804 | 788 | 788 | 788 |
| Adjusted R ² | 0.032 | 0.031 | 0.032 | 0.021 | 0.016 | 0.020 |
| Panel B: 2020:Q2 | | | | | | |
| Distress _t | 0.095*** (0.025) | 0.139*** (0.035) | 0.240*** (0.047) | 0.200*** (0.070) | 0.187* (0.103) | 0.417*** (0.133) |
| Cash Holdings _t | 0.084 (0.057) | | 0.218*** (0.067) | 0.333** (0.169) | | 0.531*** (0.198) |
| Distress _t × 2020:Q2 | | -0.097** (0.044) | -0.188*** (0.052) | | -0.076 (0.126) | -0.283* (0.148) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 804 | 804 | 804 | 788 | 788 | 788 |
| Adjusted R ² | 0.032 | 0.035 | 0.047 | 0.021 | 0.016 | 0.024 |
| Panel C: 2020:Q3 | | | | | | |
| Distress _t | 0.095*** (0.025) | 0.081*** (0.022) | 0.096*** (0.025) | 0.200*** (0.070) | 0.131** (0.064) | 0.194*** (0.070) |
| Cash Holdings _t | 0.084 (0.057) | | 0.080 (0.057) | 0.333** (0.169) | | 0.354** (0.170) |
| Distress _t × 2020:Q3 | | -0.102 (0.128) | -0.082 (0.129) | | 0.299 (0.368) | 0.390 (0.370) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 804 | 804 | 804 | 788 | 788 | 788 |
| Adjusted R ² | 0.032 | 0.030 | 0.031 | 0.021 | 0.017 | 0.021 |

Table 4. **Drawdowns and Liquidity Distress.** This table shows the results of the baseline models in equation (5). The dependent variable in columns (1) to (3) is credit line drawdowns scaled by total assets. The dependent variable in columns (4) to (6) is credit lines usage. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between distress and time dummies (2020:Q1-Q3). Panel A shows the interaction between distress and 2020:Q1. Panel B shows the interaction between distress and 2020:Q2. Panel C shows the interaction between the and 2020:Q3. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-----------------------------|----------------------|---------------------|-------------------|---------------------|---------------------|----------------------|--------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Distress | Medium Distress | High Distress | All Firms | Low Distress | Medium Distress | High Distress |
| $Distress_t$ | 0.240*** (0.047) | 0.368** (0.156) | -0.038 (0.151) | 0.830*** (0.109) | 0.417*** (0.133) | 1.347*** (0.428) | -0.916* (0.470) | 0.990*** (0.307) |
| $Distress_t \times 2020:Q2$ | -0.188*** (0.052) | -0.360** (0.158) | -0.133 (0.403) | 0.119 (0.254) | -0.283* (0.148) | -1.302*** (0.434) | 0.189 (1.252) | 0.524 (0.713) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 804 | 238 | 416 | 148 | 788 | 231 | 410 | 145 |
| Adjusted R^2 | 0.047 | 0.076 | 0.021 | 0.383 | 0.024 | 0.085 | 0.052 | 0.186 |

Table 5. **Credit Lines Drawdowns and Distress by Firm Types.** This table shows the results of the baseline models in equation (5) within different sub-samples based on firm types. The dependent variable in columns (1) to (4) is credit line drawdowns scaled by total assets. The dependent variable in columns (5) to (8) is the usage of credit lines. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between the distress and time dummies ($2020:Q2$). Apart from the whole sample (columns (1) and (5)), the regression is also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

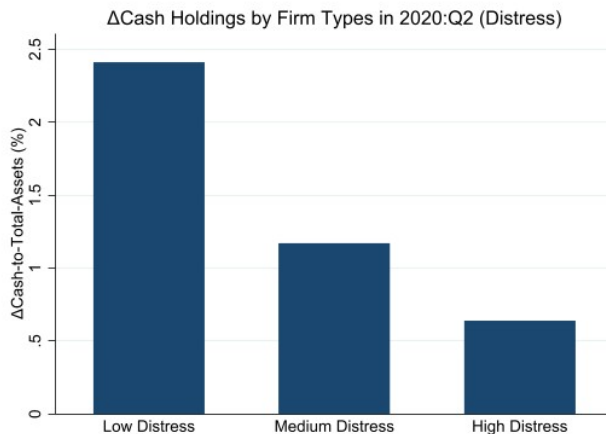


Figure 7. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current scale less the previous one, against different firm types based on financial constraint (distress). The horizontal axis shows three types of firms: Low Distress (25%), Medium Distress (50%) and High Distress (25%). The vertical axis shows the changes in percentage. Low Distress firms have the highest changes in cash holdings (2.4%), which are nearly twice as high as Medium Distress firms (1.2%) and three times as high as High Distress (0.7%) firms on average.

3.4 Shortfall in Revenue and Credit Lines Drawdowns

Why did less financially constrained firms draw down credit lines in 2020:Q2? In this section, we investigate this question. The previous literature suggests that profitable firms draw down credit lines, while non-profitable firms rely mainly on internal liquidity. We conjecture that firms with good solvency and liquidity positions saw a significant shortfall in revenue (or cash flow) and drew down their credit lines to pile up cash. A shortfall in revenue, following the COVID-19 shock, can have significant effects on firm's financing requirements. Therefore, the panic borrowing is likely to be the consequence of the unexpected shortfall in revenue. We are not aware of other studies which explicitly study this for the COVID-19 period. We use cash flow as measured by the EBITDA, net income with interests, taxes, depreciation, and amortization and include time and industry fixed

effects:

$$\text{Drawdown}_{i,t} = \beta_0 + \beta_1 \text{EBITDA}_{i,t} + \beta_2 \text{EBITDA}_{i,t} \times 2020:Q2 + \gamma X_{i,t} + \epsilon_{i,t} \quad (6)$$

where *Drawdown* is a ratio with respect firms’ non-cash total assets and *2020:Q2* is a dummy indicating the pandemic period. The specification includes a set of controls $X_{i,t}$ containing cash holding, financial constraints, the undrawn amount of credit lines, tangible assets scaled by the non-cash assets, the natural logarithm of non-cash assets, the price-to-book ratio, and the leverage ratio. Time and industry fixed effects are included. We consider firms with at least one observation before and after 2020:Q2.¹¹

We show the results using contemporaneous and lagged specifications in Table (6) and Table (7), respectively, and we also include three dummies, one for each quarter. We use all the firms in column (1), firms with low financial distress in column (2) and the ones with high financial distress in column (3). [Sufi \(2009\)](#) and [Berrospide & Meisenzahl \(2015\)](#) show that profitable firms draw down credit lines as these are likely to meet covenants imposed by banks. However, they use data from a period when credit is abundant. Following [Acharya et al. \(2012\)](#), we expect the β_1 to be negative and significant, indicating a negative association between cash flow and credit line drawdowns. Cash flow at time $t - 1$ has a significant and negative impact on credit lines drawdowns. Results using credit line usage are summarized in columns (4) to (6). We note marginally significant cash holdings for very few cases. Overall these results are similar both using lags and contemporaneous specifications and support the assumption that, at the start of the pandemic shock, an unexpected fall in revenue led firms, with good liquidity (solvency) positions, to draw down credit lines. In a nutshell, these results support the conjecture that the “panic borrowing” in Europe in 2020Q2 very significant. In the next section, we show that the “panic borrowing” following the unexpected (largely unknown) shock affected large part of the European economy.

To further shed light on these results, in Table (8), we divided firms into Lower, Medium and High EBITDA. In 2020:Q2, the dummy coefficient is only significant for firms with lower EBITDA, and this coefficient carries a negative sign. Therefore, in 2020:Q2, firms whose cash flow was expected to be hit by the COVID-19 shock, drew down their credit lines and increased cash holdings. While these results support the “panic borrowing” status, they also point towards the possibility of an endogenous role of credit lines drawdowns in firms’ decisions. We shall consider this in the next sections. Figure (8) shows, for the three groups, the change in cash holdings between 2020:Q1 and 2020:Q2. The low EBITDA group shows the most considerable change in cash holdings. The right diagram shows that low-risk firms (low solvency risk firms) experienced the most significant drop in EBITDA in 2020:Q2.

3.5 Credit Lines Drawdowns and Revenues: a Discontinuity Analysis

We discussed that the “panic borrowing” showed earlier may point towards endogeneity in firms’ decisions to draw down credit lines. This is an important issue which has important theoretical implications. We have yet to be aware of empirical studies which have addressed this issue explicitly.

¹¹Results not included in this paper show that, they remain consistent after accounting for survival bias particularly when a certain fraction of firms face bankruptcies. These results are available upon request

| | Credit Line Drawdowns | | | Credit line Usage | | |
|-------------------------------|-----------------------|---------------------|---------------------|---------------------|---------------------|-----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All Firms | Low Distress | High Distress | All Firms | Low Distress | High Distress |
| Panel A: 2020:Q1 | | | | | | |
| EBITDA _t | -0.198 (0.143) | -0.176 (0.149) | 0.157 (0.617) | -0.993** (0.410) | -0.959** (0.422) | -0.081 (1.888) |
| EBITDA _t × 2020:Q1 | 0.069 (0.827) | 0.023 (0.858) | 4.529 (4.483) | 0.791 (2.374) | 0.147 (2.421) | 19.950 (13.709) |
| Cash Holdings _t | 0.033 (0.054) | 0.033 (0.058) | 0.033 (0.214) | 0.281* (0.160) | 0.275 (0.171) | 0.359 (0.659) |
| Leverage _t | 0.071*** (0.026) | 0.077*** (0.028) | 0.067 (0.093) | 0.177** (0.073) | 0.215*** (0.077) | 0.061 (0.291) |
| log(P/B) _t | -0.005 (0.005) | -0.006 (0.006) | 0.026 (0.022) | -0.018 (0.016) | -0.024 (0.016) | 0.054 (0.069) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 781 | 687 | 94 | 767 | 675 | 92 |
| Adjusted R ² | 0.022 | 0.022 | 0.088 | 0.028 | 0.030 | 0.170 |
| Panel B: 2020:Q2 | | | | | | |
| EBITDA _t | -0.129 (0.144) | -0.138 (0.150) | 0.969 (0.682) | -0.788* (0.416) | -0.903** (0.426) | 2.872 (2.078) |
| EBITDA _t × 2020:Q2 | -1.198** (0.514) | -0.922 (0.642) | -2.822** (1.189) | -3.139** (1.458) | -1.216 (1.784) | -10.093*** (3.631) |
| Cash Holdings _t | 0.028 (0.053) | 0.035 (0.057) | -0.053 (0.209) | 0.262 (0.159) | 0.277 (0.170) | 0.014 (0.639) |
| Leverage _t | 0.069*** (0.025) | 0.077*** (0.028) | 0.056 (0.091) | 0.172** (0.072) | 0.215*** (0.077) | 0.019 (0.281) |
| log(P/B) _t | -0.004 (0.005) | -0.006 (0.006) | 0.032 (0.022) | -0.014 (0.015) | -0.024 (0.016) | 0.080 (0.066) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 781 | 687 | 94 | 767 | 675 | 92 |
| Adjusted R ² | 0.029 | 0.025 | 0.141 | 0.034 | 0.031 | 0.229 |
| Panel C: 2020:Q3 | | | | | | |
| EBITDA _t | -0.202 (0.144) | -0.160 (0.149) | -0.293 (0.671) | -0.930** (0.414) | -0.826* (0.421) | -1.311 (2.074) |
| EBITDA _t × 2020:Q2 | 0.144 (0.600) | -0.599 (0.714) | 2.572* (1.508) | -1.188 (1.699) | -4.488** (1.985) | 7.329 (4.656) |
| Cash Holdings _t | 0.032 (0.053) | 0.036 (0.058) | -0.037 (0.213) | 0.280* (0.160) | 0.299* (0.170) | 0.127 (0.661) |
| Leverage _t | 0.072*** (0.026) | 0.076*** (0.028) | 0.106 (0.094) | 0.175** (0.073) | 0.211*** (0.077) | 0.176 (0.298) |
| log(P/B) _t | -0.005 (0.005) | -0.006 (0.006) | 0.033 (0.022) | -0.016 (0.015) | -0.021 (0.016) | 0.078 (0.069) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 781 | 687 | 94 | 767 | 675 | 92 |
| Adjusted R ² | 0.022 | 0.023 | 0.111 | 0.029 | 0.038 | 0.174 |

Table 6. **Credit Lines Drawdowns and EBITDA (Contemporaneous specification)** The table shows firms' reliance on credit lines (columns 1-3) and credits line usages (columns 3-6) where both contemporaneous and lagged specifications are included in Panels A and B, respectively. We use industry, firm, country and time fixed effects. The leverage covariate is the total leverage and log(P/B) is the natural logarithm of price-to-book ratio. Columns (1) and (4) show the estimation results for all the firms whereas columns (2) and (5) show the results for firms with lower financial distress and columns (3) and (6) show the results for firms with higher financial distress. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Credit Line Drawdowns | | | Credit line Usage | | |
|---------------------------------|-----------------------|--------------|---------------|-------------------|--------------|---------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All Firms | Low Distress | High Distress | All Firms | Low Distress | High Distress |
| Panel A: 2020:Q1 | | | | | | |
| EBITDA _{t-1} | -0.447* | -0.575* | 0.571 | -1.978** | -4.367*** | 2.150 |
| | (0.245) | (0.342) | (0.784) | (0.936) | (1.403) | (2.526) |
| EBITDA _{t-1} × 2020:Q1 | -0.097 | 0.497 | -4.070** | 0.086 | 4.123** | -10.974* |
| | (0.414) | (0.499) | (1.991) | (1.573) | (2.054) | (6.316) |
| Cash Holdings _{t-1} | 0.137** | 0.108 | 0.112 | 0.396 | 0.401 | 0.497 |
| | (0.070) | (0.078) | (0.181) | (0.268) | (0.330) | (0.585) |
| Leverage _{t-1} | 0.040 | 0.026 | 0.089 | 0.185* | 0.224* | 0.159 |
| | (0.027) | (0.028) | (0.089) | (0.101) | (0.114) | (0.286) |
| log(P/B) _{t-1} | 0.003 | 0.003 | 0.019 | -0.010 | -0.003 | 0.007 |
| | (0.006) | (0.007) | (0.018) | (0.025) | (0.029) | (0.064) |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 389 | 294 | 95 | 381 | 289 | 92 |
| Adjusted R ² | 0.060 | 0.031 | 0.129 | 0.033 | 0.059 | 0.173 |
| Panel B: 2020:Q2 | | | | | | |
| EBITDA _{t-1} | -0.416** | -0.227 | -0.202 | -1.732** | -2.214* | -0.149 |
| | (0.211) | (0.277) | (0.742) | (0.805) | (1.160) | (2.340) |
| EBITDA _{t-1} × 2020:Q2 | -0.915 | -1.555** | 3.175 | -3.325 | -5.100 | 12.341 |
| | (0.620) | (0.772) | (3.228) | (2.348) | (3.188) | (10.041) |
| Cash Holdings _{t-1} | 0.124* | 0.102 | 0.130 | 0.357 | 0.396 | 0.609 |
| | (0.069) | (0.078) | (0.195) | (0.266) | (0.331) | (0.625) |
| Leverage _{t-1} | 0.042 | 0.031 | 0.045 | 0.193* | 0.239** | 0.018 |
| | (0.027) | (0.028) | (0.091) | (0.101) | (0.115) | (0.291) |
| log(P/B) _{t-1} | 0.004 | 0.003 | 0.021 | -0.006 | -0.011 | 0.015 |
| | (0.006) | (0.006) | (0.019) | (0.024) | (0.028) | (0.064) |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 389 | 294 | 95 | 381 | 289 | 92 |
| Adjusted R ² | 0.065 | 0.042 | 0.091 | 0.038 | 0.054 | 0.155 |
| Panel C: 2020:Q3 | | | | | | |
| EBITDA _{t-1} | -0.588*** | -0.342 | -1.071 | -2.425*** | -2.590** | -1.846 |
| | (0.226) | (0.289) | (1.007) | (0.858) | (1.213) | (3.239) |
| EBITDA _{t-1} × 2020:Q3 | 0.532 | -0.142 | 2.244 | 2.316 | -0.487 | 4.767 |
| | (0.432) | (0.612) | (1.581) | (1.640) | (2.551) | (5.031) |
| Cash Holdings _{t-1} | 0.138** | 0.114 | 0.061 | 0.414 | 0.447 | 0.314 |
| | (0.069) | (0.079) | (0.182) | (0.265) | (0.333) | (0.587) |
| Leverage _{t-1} | 0.045* | 0.026 | 0.113 | 0.207** | 0.225* | 0.187 |
| | (0.027) | (0.028) | (0.096) | (0.102) | (0.115) | (0.305) |
| log(P/B) _{t-1} | 0.002 | 0.002 | 0.025 | -0.013 | -0.015 | 0.033 |
| | (0.006) | (0.006) | (0.018) | (0.024) | (0.028) | (0.064) |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 389 | 294 | 95 | 381 | 289 | 92 |
| Adjusted R ² | 0.064 | 0.028 | 0.104 | 0.038 | 0.045 | 0.148 |

Table 7. **Credit Lines Drawdowns and EBITDA (Lagged specification)** The table shows firms' reliance on credit lines (columns 1-3) and credits line usages (columns 3-6) where both contemporaneous and lagged specifications are included in Panels A and B, respectively. We use industry, firm, country and time fixed effects. The leverage covariate is the total leverage and log(P/B) is the natural logarithm of price-to-book ratio. Columns (1) and (4) show the estimation results for all the firms whereas columns (2) and (5) show the results for firms with lower financial distress and columns (3) and (6) show the results for firms with higher financial distress. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-------------------------------|----------------------|---------------------|----------------------|----------------------|----------------------|---------------------|-----------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low EBITDA | Medium EBITDA | High EBITDA | All Firms | Low EBITDA | Medium EBITDA | High EBITDA |
| EBITDA _t | -0.315** (0.138) | 0.278 (0.322) | -2.706*** (0.805) | -0.823** (0.322) | -1.209*** (0.431) | 0.735 (0.966) | -10.151*** (2.627) | -1.395 (0.956) |
| EBITDA _t × 2020:Q2 | -1.357*** (0.475) | -2.760** (1.181) | 3.163 (3.037) | 0.427 (1.554) | -3.327** (1.446) | -7.400** (3.413) | 18.228* (9.816) | -0.685 (4.503) |
| log(Assets) _t | -0.006*** (0.002) | -0.006 (0.004) | -0.005** (0.002) | -0.011*** (0.004) | -0.022*** (0.005) | -0.036** (0.014) | -0.019** (0.008) | -0.027** (0.010) |
| Leverage _t | 0.077*** (0.023) | -0.001 (0.067) | 0.074** (0.031) | 0.121** (0.047) | 0.146** (0.071) | 0.081 (0.198) | 0.130 (0.102) | 0.220 (0.137) |
| P/B _t | 0.000 (0.001) | -0.011* (0.006) | 0.001 (0.002) | 0.002 (0.002) | 0.001 (0.004) | -0.008 (0.017) | 0.009 (0.007) | 0.004 (0.006) |
| Undrawn CL _t | 0.367*** (0.034) | 0.504*** (0.083) | 0.443*** (0.053) | 0.211*** (0.056) | -0.261** (0.105) | -0.293 (0.244) | -0.407** (0.173) | -0.086 (0.163) |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 781 | 186 | 389 | 206 | 767 | 180 | 382 | 205 |
| Adjusted R ² | 0.177 | 0.220 | 0.201 | 0.156 | 0.057 | 0.062 | 0.060 | 0.114 |

Table 8. **Credit Lines Drawdowns and EBITDA by firm types.** This table shows the results of the baseline models in equation (5) within different sub-samples based on firm types. The dependent variable in columns (1) to (4) is credit line drawdowns scaled by total assets. The dependent variable in columns (5) to (8) is the usage of credit lines. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between the distress and time dummies (2020:Q2). Apart from the whole sample (columns (1) and (5)), the regression is also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

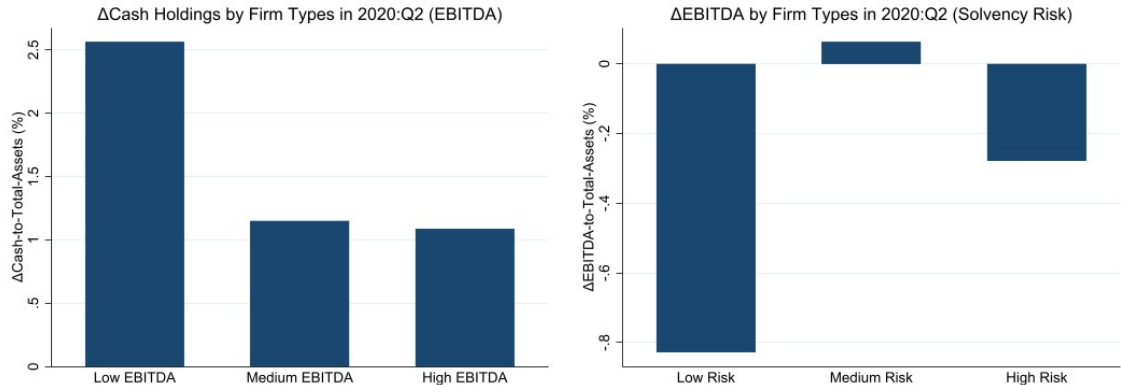


Figure 8. The diagram on the left-hand-side shows the aggregate percentage change in firms cash holdings to total assets ratio by the underlying earning status, low, medium and high, respectively, which shows firms within the lowest status increased their cash holdings relatively twice the other groups between the 2020:Q1-Q2. The diagram on the right-hand-side shows the aggregate percentage changes in the earnings between 2020:Q1-Q2 according to the firms underlying risk profiles.

This section uses a novel econometric approach to study this issue.

We use a quasi experimental analysis to investigate firms' decisions to access credit lines around a defined break-even earning neighbourhood using the following specification:

$$\text{Drawdown}_{i,t} = \beta_0 + \beta_1 D_{i,t}(\lambda) + \beta_2 D_{i,t}(\lambda) \times 2020:Q2 + \gamma X_{i,t} + \epsilon_{i,t} \quad (7)$$

where λ denotes the choice of neighbourhood bandwidth such that D_i is equal to a firm performance outcome within $[0, \lambda)$ bandwidth and zero otherwise.¹² The notations follow the definition in equation (6), and consider firms with at least one observation before and after 2020:Q2. The

¹²We use set a range of values for the bandwidth as in Chava & Roberts (2008) and Hoxby (2000). These papers provide a comprehensive discussion about the choice of bandwidth.

identification exploits a subsample of the firm-level data within the bandwidth, to study a discontinuity across credit line drawdown decisions within a neighbourhood. Performance outcomes across firms within the neighbourhood provide a quasi-randomisation experiment as realisations just above or below the zero thresholds drive firms' decisions to draw down credit lines. We expect that firms with performance just above the zero thresholds tend to behave differently from those with realisations just below the threshold.

The results are presented in Table (9), where we consider five bandwidths between 0.25-1.25 (columns (1) to (10)) multiplied by the EBITDA standard deviation. Take columns (1), (3), (5), (7), and (9) as an example. The coefficients on the dummy 2020Q2 are highly significant and negative for these values. They also decline in size from -1.071 to -0.722, that is, a 1.071 to 0.722 percentage point decrease in credit lines draw down to total assets ratio in response to a one percentage point increase in EBITDA-to-total assets ratio. Firms with marginally positive performance rely less on credit lines. Their performance and expected revenue, as measured by EBITDA, are important to understand why using credit lines during the COVID-19 shock. These results confirm that during the pandemic shock, firms exhibited a shift in their drawdown decisions due to a shortfall in revenue. However, these results contrast with [Sufi \(2009\)](#) and [Campello et al. \(2011\)](#), who find that more profitable firms draw down credit lines. The empirical evidence in support of the "panic borrowing" is quite robust and seems to be driven by a shortfall in firms' revenue.¹³

¹³Appendix (D) shows an alternative design of regression discontinuity where we show that the empirical evidence in Table (9) is robust.

| | Dependent Variable: Drawdown Size | | | | | | | | | |
|-------------------------------|-----------------------------------|---------------------|----------------------|----------------------|---------------------|----------------------|---------------------|----------------------|---------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| EBITDA _t | 0.146 (0.410) | -1.071** (0.510) | -0.112 (0.386) | -1.002*** (0.368) | -0.326 (0.401) | -0.869*** (0.291) | -0.257 (0.354) | -0.784*** (0.256) | -0.194 (0.344) | -0.722*** (0.253) |
| EBITDA _t × 2020:Q2 | -3.173*** (1.005) | 0.873 (3.851) | -2.778*** (0.975) | 0.430 (1.236) | -2.316** (1.000) | -0.398 (1.008) | -2.343** (0.974) | -1.293 (0.909) | -2.507** (0.967) | -1.305 (0.928) |
| log(Assets _t) | 0.000 (0.007) | -0.012** (0.006) | -0.005 (0.006) | -0.009** (0.004) | -0.005 (0.005) | -0.012*** (0.003) | -0.005 (0.005) | -0.008*** (0.003) | -0.005 (0.005) | -0.009*** (0.003) |
| Leverage _t | 0.085 (0.067) | 0.090 (0.060) | 0.125* (0.065) | 0.078* (0.040) | 0.135** (0.063) | 0.077** (0.032) | 0.145** (0.061) | 0.068** (0.028) | 0.111* (0.059) | 0.064** (0.028) |
| Undrawn CL _t | 0.337*** (0.098) | 0.425*** (0.091) | 0.312*** (0.089) | 0.352*** (0.066) | 0.287*** (0.091) | 0.263*** (0.052) | 0.284*** (0.090) | 0.283*** (0.046) | 0.271*** (0.088) | 0.243*** (0.042) |
| log(Price _t) | 0.003 (0.012) | 0.007 (0.009) | 0.005 (0.010) | 0.009 (0.006) | 0.000 (0.009) | 0.004 (0.005) | 0.001 (0.009) | 0.001 (0.004) | 0.002 (0.008) | 0.003 (0.004) |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 85 | 110 | 115 | 213 | 149 | 309 | 157 | 387 | 169 | 427 |
| Adjusted R ² | 0.237 | 0.267 | 0.253 | 0.208 | 0.150 | 0.153 | 0.148 | 0.148 | 0.121 | 0.133 |

Table 9. **Regression Discontinuity Design and Credit Lines Drawdowns.** This table shows credit line drawdowns on revenue within various groups based on cash flow. The dependent variable is *Drawdown Size*, is credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included. Columns (1), (3), (5), (7), and (9) use subsamples based on the performance just below the threshold. The rest columns use subsamples based on the performance just above the threshold. σ denotes the standard deviation of the performance. A real number multiplying σ (for example, -0.5σ) represents the direction and distance away from the threshold. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 European firms During the 2008-2012 Crises

Is the “panic borrowing” unique to the pandemic crisis? Answering this question is important to understand if a type of shock matters to understand firms’ preference for credit lines drawdowns and cash accumulation. To address this question, we compare the impact of the COVID-19 shock with that of the 2008 - 2012 financial and European crises. Of course, these two shocks are very different as the former originated in the financial market and affected the banking system, while the latter did not. There is a large amount of literature documenting the impact of the 2008 financial crisis on US corporate decisions, particularly on the relationship between cash holdings (cash) and financial constraints. Our paper also speaks to this part of the literature but focuses mainly on credit line drawdowns.

4.1 European Firms and The Financial Crisis

4.1.1 The 2008 Financial Crisis and Credit Lines Drawdowns

In Table (10) to Table (12), we use solvency and liquidity constraints and study if European firms’ hit by the 2008 financial crisis drew down their credit lines. We show the results for 2008:Q2-2008:Q4 period.

In general, if we consider all the firms, there is a negative association between firms’ solvency (Table (10)), liquidity (Table (11)) risk, and credit lines drawdowns. Furthermore, there is weak evidence that the financial crisis’s shock is associated with European firms’ decisions to draw down credit lines. For all the firms, there is evidence that they reduced access to their credit lines regardless of their solvency or liquidity status. In a nutshell, there is weak evidence that the 2008 financial crisis, differently than what documented for the US, acted as a detonator leading to a dash for cash.¹⁴

4.1.2 The 2012 European Crisis and Credit Lines Drawdowns

We now turn to the European crisis. This comparison should help us understand if there are any significant differences in corporate decisions under these two very different crises. We show the results in Table (13) to Table (15).

Firms’ solvency risk is not always significant and is negatively associated with firms’ decisions to draw down credit lines. The empirical evidence is also weak when liquidity constraints is introduced (Table (14)) and also for firms hit by a shortfall in revenue (Table (15)). Overall, there is weak evidence that the 2012 European crisis acted as a detonator for firms to dash for cash. These results show that the COVID-19 shock is unique. Following that shock, European firms drew down their credit lines for precautionary motives driven by a “panic borrowing”.¹⁵ Finally, our results contrast with the extensive literature on financial constraints during the 2008 financial crisis and the dash for cash of US firms (Sufi 2009).

¹⁴We also used Cash Holdings in Table (10). Cash holding is generally significant and positive for RID but insignificant and negative for liquidity distress. This seems to suggest weak evidence of cash holdings accumulation for European firms during the financial crisis.) In Table (12) coefficients are all generally highly significant, but while with RID, they carry a positive sign. These are negative in the case of Distress and EBITDA.

¹⁵We also include Cash Holdings in Table (13) to Table (15) and while the coefficients are generally highly significant, once again, are positive for RID and negative for Distress and EBITDA.

| | Drawdown Size | | | | Credit Line Usage | | | |
|------------------------------|----------------------|---------------------|-------------------|---------------------|----------------------|----------------------|----------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Risk | Medium Risk | High Risk | All Firms | Low Risk | Medium Risk | High Risk |
| Panel A: 2008:Q2 | | | | | | | | |
| RID _{t-1} | -0.072*** (0.014) | -0.094** (0.045) | -0.059 (0.042) | -0.080 (0.089) | -0.151*** (0.032) | -0.263*** (0.083) | -0.358*** (0.132) | -0.086 (0.236) |
| RID _{t-1} × 2008:Q2 | -0.030 (0.051) | -0.238 (0.408) | 0.066 (0.132) | -0.436** (0.175) | -0.127 (0.118) | -0.555 (0.745) | 0.298 (0.419) | -0.737 (0.463) |
| Observations | 498 | 106 | 254 | 138 | 500 | 107 | 255 | 138 |
| Adjusted R ² | 0.203 | 0.155 | 0.161 | 0.346 | 0.209 | 0.248 | 0.195 | 0.308 |
| Panel B: 2008:Q3 | | | | | | | | |
| RID _{t-1} | -0.072*** (0.014) | -0.095** (0.045) | -0.056 (0.043) | -0.095 (0.091) | -0.154*** (0.032) | -0.266*** (0.082) | -0.348** (0.135) | -0.116 (0.238) |
| RID _{t-1} × 2008:Q3 | -0.014 (0.046) | -0.168 (0.285) | 0.013 (0.109) | -0.113 (0.174) | -0.048 (0.107) | -0.411 (0.519) | 0.113 (0.345) | -0.100 (0.456) |
| Observations | 498 | 106 | 254 | 138 | 500 | 107 | 255 | 138 |
| Adjusted R ² | 0.202 | 0.155 | 0.160 | 0.313 | 0.208 | 0.249 | 0.194 | 0.293 |
| Panel C: 2008:Q4 | | | | | | | | |
| RID _{t-1} | -0.076*** (0.014) | -0.112** (0.046) | -0.051 (0.042) | -0.102 (0.091) | -0.163*** (0.033) | -0.303*** (0.084) | -0.284** (0.131) | -0.120 (0.238) |
| RID _{t-1} × 2008:Q4 | 0.027 (0.037) | 0.149 (0.130) | -0.042 (0.142) | -0.091 (0.187) | 0.071 (0.086) | 0.308 (0.237) | -0.709 (0.447) | 0.042 (0.488) |
| Observations | 498 | 106 | 254 | 138 | 500 | 107 | 255 | 138 |
| Adjusted R ² | 0.203 | 0.165 | 0.161 | 0.312 | 0.209 | 0.259 | 0.202 | 0.293 |

Table 10. **Credit Lines Drawdowns and Solvency Risk in 2008 Financial Crisis.** This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the RID ratio and *2008:Q2*, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the RID ratio and *2008:Q3*, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the RID ratio and *2008:Q4*, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|---------------------------------|-------------------|-------------------|---------------------|--------------------|--------------------|--------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Distress | Medium Distress | High Distress | All Firms | Low Distress | Medium Distress | High Distress |
| Panel A: 2008:Q2 | | | | | | | | |
| Distress _t | -0.041 (0.036) | 0.112 (0.082) | -0.310** (0.154) | -0.016 (0.079) | -0.123 (0.091) | 0.414* (0.229) | -0.158 (0.384) | -0.253 (0.190) |
| Distress _t × 2008:Q2 | 0.001 (0.070) | -0.057 (0.096) | 0.543 (0.595) | -0.299 (0.288) | -0.054 (0.176) | -0.248 (0.269) | 0.542 (1.484) | -0.498 (0.696) |
| Observations | 916 | 250 | 450 | 215 | 917 | 250 | 451 | 215 |
| Adjusted R ² | 0.081 | 0.119 | 0.063 | 0.173 | 0.133 | 0.122 | 0.097 | 0.232 |
| Panel B: 2008:Q3 | | | | | | | | |
| Distress _t | -0.037 (0.036) | 0.113 (0.082) | -0.270* (0.156) | -0.043 (0.080) | -0.117 (0.091) | 0.409* (0.228) | -0.199 (0.388) | -0.286 (0.194) |
| Distress _t × 2008:Q3 | -0.059 (0.067) | -0.082 (0.089) | -0.211 (0.529) | 0.069 (0.234) | -0.128 (0.169) | -0.263 (0.248) | 0.950 (1.316) | 0.003 (0.566) |
| Observations | 916 | 250 | 450 | 215 | 917 | 250 | 451 | 215 |
| Adjusted R ² | 0.082 | 0.121 | 0.062 | 0.169 | 0.133 | 0.123 | 0.098 | 0.230 |
| Panel C: 2008:Q4 | | | | | | | | |
| Distress _t | -0.058 (0.038) | 0.082 (0.084) | -0.335** (0.168) | -0.140 (0.087) | -0.168* (0.096) | 0.255 (0.233) | -0.467 (0.418) | -0.413* (0.212) |
| Distress _t × 2008:Q4 | 0.066 (0.048) | 0.078 (0.067) | 0.221 (0.317) | 0.404** (0.167) | 0.165 (0.120) | 0.430** (0.187) | 1.448* (0.787) | 0.492 (0.408) |
| Observations | 916 | 250 | 450 | 215 | 917 | 250 | 451 | 215 |
| Adjusted R ² | 0.083 | 0.123 | 0.062 | 0.193 | 0.134 | 0.138 | 0.104 | 0.236 |

Table 11. **Credit Lines Drawdowns and Liquidity Distress in 2008 Financial Crisis.** This table shows the results of the baseline models in equation (5) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the liquidity distress and *2008:Q2*, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the distress and *2008:Q3*, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the distress and *2008:Q4*, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Distress Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-------------------------------|---------------------|-------------------|-------------------|-------------------|--------------------|--------------------|-------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low EBITDA | Medium EBITDA | High EBITDA | All Firms | Low EBITDA | Medium EBITDA | High EBITDA |
| Panel A: 2008:Q2 | | | | | | | | |
| EBITDA _t | -0.224** (0.096) | -0.373 (0.320) | -0.803 (0.573) | -0.041 (0.170) | -0.409 (0.261) | -1.123 (0.830) | -0.735 (1.451) | 0.831 (0.587) |
| EBITDA _t × 2008:Q2 | 0.140 (0.342) | -0.032 (0.998) | -1.342 (2.043) | 0.176 (0.493) | 0.304 (0.925) | 0.726 (2.602) | -2.981 (5.173) | 0.415 (1.705) |
| Observations | 818 | 205 | 427 | 185 | 819 | 206 | 427 | 185 |
| Adjusted R ² | 0.132 | 0.134 | 0.225 | 0.097 | 0.133 | 0.130 | 0.270 | 0.054 |
| Panel B: 2008:Q3 | | | | | | | | |
| EBITDA _t | -0.220** (0.096) | -0.422 (0.318) | -0.828 (0.574) | -0.042 (0.171) | -0.427 (0.260) | -1.189 (0.828) | -0.948 (1.453) | 0.900 (0.592) |
| EBITDA _t × 2008:Q3 | 0.078 (0.352) | 1.715 (1.411) | -0.966 (2.148) | 0.159 (0.531) | 0.646 (0.953) | 3.391 (3.686) | 0.410 (5.440) | -0.545 (1.836) |
| Observations | 818 | 205 | 427 | 185 | 819 | 206 | 427 | 185 |
| Adjusted R ² | 0.132 | 0.141 | 0.225 | 0.096 | 0.133 | 0.133 | 0.269 | 0.055 |
| Panel C: 2008:Q4 | | | | | | | | |
| EBITDA _t | -0.253** (0.115) | -0.604 (0.379) | -0.979 (0.631) | 0.011 (0.209) | -0.592* (0.311) | -1.666* (0.988) | -0.850 (1.597) | 0.396 (0.720) |
| EBITDA _t × 2008:Q4 | 0.109 (0.190) | 0.579 (0.525) | 0.431 (1.371) | -0.100 (0.311) | 0.577 (0.513) | 1.418 (1.364) | -0.341 (3.471) | 1.142 (1.073) |
| Observations | 818 | 205 | 427 | 185 | 819 | 206 | 427 | 185 |
| Adjusted R ² | 0.132 | 0.140 | 0.225 | 0.096 | 0.134 | 0.135 | 0.269 | 0.061 |

Table 12. **Credit Lines Drawdowns and Cash Flow During the 2008 Financial Crisis.** This table shows the results of the baseline models in equation (6) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the EBITDA and 2008:Q2, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the EBITDA and 2008:Q3, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the EBITDA and 2008:Q4, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low*-, *Medium*-, and *High-EBITDA Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|------------------------------|--------------------|-------------------|---------------------|-------------------|-------------------|-------------------|-------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Risk | Medium Risk | High Risk | All Firms | Low Risk | Medium Risk | High Risk |
| Panel A: 2012:Q2 | | | | | | | | |
| RID _{t-1} | 0.006** (0.003) | 0.004 (0.003) | -0.082** (0.037) | -0.008 (0.047) | 0.012* (0.007) | 0.007 (0.008) | -0.057 (0.090) | 0.037 (0.115) |
| RID _{t-1} × 2012:Q2 | -0.003 (0.011) | 0.003 (0.014) | 0.091 (0.172) | 0.239 (0.173) | -0.006 (0.027) | 0.002 (0.032) | 0.173 (0.417) | 0.404 (0.422) |
| Observations | 1493 | 450 | 657 | 385 | 1497 | 452 | 658 | 386 |
| Adjusted R ² | 0.220 | 0.300 | 0.273 | 0.092 | 0.149 | 0.247 | 0.161 | 0.127 |
| Panel B: 2012:Q3 | | | | | | | | |
| RID _{t-1} | 0.006** (0.003) | 0.005 (0.004) | -0.086** (0.037) | 0.011 (0.047) | 0.011 (0.007) | 0.008 (0.008) | -0.074 (0.090) | 0.036 (0.114) |
| RID _{t-1} × 2012:Q3 | -0.002 (0.009) | -0.001 (0.011) | 0.166 (0.165) | -0.067 (0.170) | 0.007 (0.021) | -0.006 (0.024) | 0.572 (0.398) | 0.418 (0.415) |
| Observations | 1493 | 450 | 657 | 385 | 1497 | 452 | 658 | 386 |
| Adjusted R ² | 0.220 | 0.300 | 0.274 | 0.088 | 0.149 | 0.247 | 0.163 | 0.127 |
| Panel C: 2012:Q4 | | | | | | | | |
| RID _{t-1} | 0.006* (0.003) | 0.004 (0.004) | -0.077** (0.038) | 0.009 (0.047) | 0.011 (0.007) | 0.004 (0.008) | -0.035 (0.092) | 0.051 (0.114) |
| RID _{t-1} × 2012:Q4 | 0.003 (0.009) | 0.007 (0.010) | -0.024 (0.141) | -0.021 (0.149) | 0.009 (0.021) | 0.029 (0.023) | -0.241 (0.340) | 0.158 (0.365) |
| Observations | 1493 | 450 | 657 | 385 | 1497 | 452 | 658 | 386 |
| Adjusted R ² | 0.220 | 0.300 | 0.273 | 0.087 | 0.149 | 0.249 | 0.161 | 0.125 |

Table 13. **Credit Lines Drawdowns and Solvency Risk During the 2012 European Crisis.** This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the RID ratio and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the RID ratio and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the RID ratio and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-, Medium-, and High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|---------------------------------|---------------------|-------------------|-------------------|-------------------|---------------------|--------------------|---------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Distress | Medium Distress | High Distress | All Firms | Low Distress | Medium Distress | High Distress |
| Panel A: 2012:Q2 | | | | | | | | |
| Distress _t | 0.072*** (0.015) | 0.022 (0.032) | 0.116* (0.065) | 0.066* (0.035) | 0.089** (0.035) | 0.128 (0.083) | 0.504*** (0.160) | 0.031 (0.073) |
| Distress _t × 2012:Q2 | -0.039 (0.050) | -0.015 (0.088) | 0.022 (0.316) | -0.207 (0.158) | -0.084 (0.117) | 0.124 (0.227) | -0.772 (0.782) | -0.332 (0.326) |
| Observations | 3232 | 814 | 1535 | 883 | 3234 | 814 | 1537 | 883 |
| Adjusted R ² | 0.110 | 0.037 | 0.115 | 0.120 | 0.116 | 0.089 | 0.086 | 0.164 |
| Panel B: 2012:Q3 | | | | | | | | |
| Distress _t | 0.071*** (0.015) | 0.023 (0.032) | 0.096 (0.065) | 0.063* (0.035) | 0.083** (0.035) | 0.132 (0.083) | 0.446*** (0.160) | 0.022 (0.073) |
| Distress _t × 2012:Q3 | -0.014 (0.045) | -0.037 (0.063) | 0.527* (0.292) | -0.135 (0.158) | 0.074 (0.106) | 0.005 (0.162) | 0.725 (0.724) | -0.149 (0.327) |
| Observations | 3232 | 814 | 1535 | 883 | 3234 | 814 | 1537 | 883 |
| Adjusted R ² | 0.110 | 0.038 | 0.116 | 0.119 | 0.116 | 0.089 | 0.086 | 0.163 |
| Panel C: 2012:Q4 | | | | | | | | |
| Distress _t | 0.069*** (0.015) | 0.014 (0.033) | 0.099 (0.066) | 0.055 (0.036) | 0.062* (0.036) | 0.099 (0.084) | 0.406** (0.164) | -0.019 (0.075) |
| Distress _t × 2012:Q4 | 0.016 (0.034) | 0.063 (0.054) | 0.179 (0.192) | 0.018 (0.107) | 0.252*** (0.080) | 0.299** (0.139) | 0.680 (0.476) | 0.311 (0.220) |
| Observations | 3232 | 814 | 1535 | 883 | 3234 | 814 | 1537 | 883 |
| Adjusted R ² | 0.110 | 0.039 | 0.115 | 0.118 | 0.119 | 0.094 | 0.086 | 0.165 |

Table 14. **Credit Lines Drawdowns and Liquidity Distress During the 2012 European Crisis.** This table shows the results of the baseline models in equation (5) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the liquidity distress and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the distress and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the distress and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-, Medium-, and High-Distress Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-------------------------------|----------------------|---------------------|-------------------|-------------------|----------------------|--------------------|------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low EBITDA | Medium EBITDA | High EBITDA | All Firms | Low EBITDA | Medium EBITDA | High EBITDA |
| Panel A: 2012:Q2 | | | | | | | | |
| EBITDA _t | -0.102** (0.040) | -0.129* (0.071) | -0.125 (0.352) | -0.018 (0.121) | -0.188* (0.104) | -0.025 (0.189) | 0.376 (0.883) | -0.484 (0.357) |
| EBITDA _t × 2012:Q2 | -0.005 (0.261) | -0.003 (0.381) | -0.450 (1.874) | 0.067 (0.929) | 0.336 (0.682) | -0.384 (1.015) | 2.498 (4.704) | -1.109 (2.744) |
| Observations | 2936 | 772 | 1469 | 695 | 2938 | 772 | 1471 | 695 |
| Adjusted R ² | 0.164 | 0.259 | 0.152 | 0.161 | 0.109 | 0.187 | 0.095 | 0.102 |
| Panel B: 2012:Q3 | | | | | | | | |
| EBITDA _t | -0.089** (0.040) | -0.110 (0.072) | -0.155 (0.354) | -0.026 (0.122) | -0.129 (0.105) | 0.024 (0.191) | 0.258 (0.888) | -0.520 (0.359) |
| EBITDA _t × 2012:Q3 | -0.309* (0.181) | -0.368 (0.237) | 0.374 (1.630) | 0.341 (0.584) | -1.262*** (0.472) | -1.125* (0.630) | 4.581 (4.091) | 0.936 (1.725) |
| Observations | 2936 | 772 | 1469 | 695 | 2938 | 772 | 1471 | 695 |
| Adjusted R ² | 0.165 | 0.262 | 0.152 | 0.162 | 0.111 | 0.191 | 0.096 | 0.102 |
| Panel C: 2012:Q4 | | | | | | | | |
| EBITDA _t | -0.116*** (0.042) | -0.153** (0.074) | -0.291 (0.366) | 0.016 (0.125) | -0.179 (0.109) | -0.139 (0.198) | 0.212 (0.918) | -0.406 (0.369) |
| EBITDA _t × 2012:Q4 | 0.125 (0.119) | 0.191 (0.182) | 1.414 (1.083) | -0.373 (0.365) | -0.026 (0.309) | 0.845* (0.483) | 2.255 (2.721) | -0.985 (1.078) |
| Observations | 2936 | 772 | 1469 | 695 | 2938 | 772 | 1471 | 695 |
| Adjusted R ² | 0.165 | 0.260 | 0.153 | 0.163 | 0.109 | 0.191 | 0.096 | 0.103 |

Table 15. **Credit Lines Drawdowns and Cash Flow During the 2012 European Crisis.** This table shows the results of the baseline models in equation (6) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the EBITDA and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the EBITDA and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the EBITDA and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-EBITDA Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Lockdown Policies, Credit Lines Drawdowns and Cash Accumulation

We showed that during the COVID-19 shock, European firms went into a “panic borrowing” driven by an unexpected sharp fall in revenue and firms with good solvency and liquidity risk drew down their credit lines and topped up their cash holdings. We also showed that this result was essentially unique to the COVID-19 crisis and had no precedent with other crises in Europe (the 2008 financial crisis and the 2012 European crisis). In the following sections, we study the differential effect of COVID-19 on European firms’ decisions to access credit lines. We investigate if European firms in different countries, hit differently by the COVID-19 shock, drew down their credit lines. We consider country’s infection data and also country’s specific social distancing policy (less or more stringent) to define country flexibility. We borrow this approach from Campello et al (2020) who studies job hiring in the US and work flexibility. The idea of doing this is twofold. Firstly, it will allow us to directly use information on reported COVID-19 cases to define the COVID-19 shock and to study if the “panic borrowing” is a consequence of high COVID-19 cases and stringent policy measures. Second, It also presents the opportunity to run additional robustness test to support the empirical results presented in the previous section and mitigate potential endogeneity issues. We measure firms’ impact of COVID-19 in two different ways. First, as explained, we follow Campello et al. (2020) and define high (low) COVID-19 impact within a specific country (we use four countries: Italy, Germany, Spain and France). We also use an alternative indicator as a proxy for social distancing strictness across European countries: the Oxford Stringency Index. A higher value of this index implies a stricter social distancing policy in that country.

4.2.1 Infection Rates, Mobility Policy and Credit Lines Drawdowns

We use Equation (8) below to study the relationship between infection rates (mobility policy) and firms’ credit lines draw downs.

$$\begin{aligned} Drawdown_{i,t} = & \alpha + \beta_1 COVID Impact_{i,t} + \beta_2 (COVID Impact_{i,t} \times 2020:Q2) \\ & + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{8}$$

where $Drawdown_{i,t}$ denotes: 1) credit line drawdowns divided by total assets, and 2) credit line usage. $COVID Impact_{i,t}$ is once 1). $High COVID Exposure_{i,t}$, a dummy equal to 1 each quarter the country is in the top 50% of the number of confirmed COVID cases per million and 0 elsewhere (Campello et al. 2020); 2) We also use $\log(Stringency)$, the logarithm of the Stringency Index which records the strictness of “lockdown style” policies. Higher Stringency Index restricts people’s access to some jobs (Ritchie et al. 2020). $2020:Q2$ is a time dummy which denotes the period of the shock. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of the price-to-book ratio. Industry fixed effect is included. The regression results of Equation (8) are documented in Table (16).

Table (16) shows that, generally, firms reduced access to credit lines during the whole sample period but increased reliance on credit lines in 2020Q2. Our results using the Stringency Index are even more supportive and show that more stringent social distancing rules lead to higher drawdowns. In a nutshell, at the peak of the COVID-19 shock, European firms facing a shortfall in revenue due to the unexpected lockdowns across Europe went into a “panic borrowing” status.

They dashed for cash by drawing down their credit lines accumulating cash. That is, the panic borrowing in Europe is driven by the unexpected shock introduced by the lockdown policies across Europe. Our results suggest that lockdown policies have introduced a new type of risk for firms' corporate liquidity risk management. This novel result is significant for future theoretical models on liquidity risk management as one would need to account for a run on credit lines, subsequently, a government policy (lockdown), which triggers cash accumulation. Finally, the results in this and previous sections point towards an endogenous role of credit lines in liquidity risk management.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-----------------------------|----------------------|----------------------|--------------------|--------------------|----------------------|----------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| High COVID Exposure | -0.066*** (0.013) | -0.078*** (0.015) | | | -0.225*** (0.043) | -0.294*** (0.049) | | |
| High COVID Exposure×2020:Q2 | | 0.022 (0.015) | | | | 0.130*** (0.049) | | |
| log(Stringency) | | | 0.037** (0.019) | 0.045** (0.019) | | | 0.161*** (0.060) | 0.183*** (0.061) |
| log(Stringency)×2020:Q2 | | | | 0.007** (0.003) | | | | 0.020* (0.010) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 211 | 211 | 211 | 211 | 206 | 206 | 206 | 206 |
| R^2 | 0.186 | 0.195 | 0.101 | 0.122 | 0.194 | 0.223 | 0.110 | 0.127 |

Table 16. **The impact of COVID-19 on Credit Line Drawdowns During the COVID-19 Shock.** This table presents the regression results of Equation (8). The dependent variable is $Drawdown_{i,t}$ which contains either credit line drawdown to total assets or the utilization of credit lines. $COVID\ Exposure_{i,t}$ represents two variables which are *High COVID Exposure* $_{i,t}$, a dummy equal to 1 that for each quarter the country belongs to the top 50% of the number of confirmed COVID cases per million and 0 elsewhere (Campello et al. 2020); 2) $\log(Stringency)$, the logarithm of the Stringency Index which records the strictness of 'lockdown style' policies that primarily restrict people's behaviour (Ritchie et al. 2020). *2020:Q2* is a time dummy which denotes the period of the shock. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of price-to-book ratio. Industry fixed effect is included. We show robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2 Social Distancing Policies Across European Countries

Given that European countries have used different mobility policies rules during the COVID-19, we want to condition the previous tests on country’s exposure to the spread of the virus and the strictness of social distancing policies. We study the relationship between social distancing rules across different countries and firms’ decisions to draw down credit lines. Is there any significant difference amongst the social distancing policies adopted within Europe which can help us to understand why firms drew down their credit lines and piled up cash? Figure (9) show the strictness of social distancing rules as measured by the Stringency Index across the four largest European economies. Italy, overall, experienced the most stringent mobility rule, followed by Germany. In this section, we investigate if the different stringent policy rules help us to understand firms’ decisions to draw down credit lines.

We construct a specification to investigate the relationship between credit line drawdowns and the strictness of lockdown policies across countries as follows:

$$\begin{aligned} Drawdown_{i,t} = & \alpha + \beta_1 \log(Stringency)_{i,t} + \beta_2 (\log(Stringency)_{i,t} \times Country_i) \\ & + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{9}$$

where $Drawdown_{i,t}$ has same definition as previous specifications. $\log(Stringency)_{i,t}$ indicates the logarithm of the Stringency Index which records the strictness of ‘lockdown style’ policies. $Country_i$ is an indicator of different countries including Italy, Germany, France, and Spain. The controls have same definitions as previous specifications. Table (17) reports the regression results of Equation (9).

The relationship between the stringency index and credit lines draw down is positive and significant across all the countries. However, the impact of the social distancing policies on credit lines draw down is different across countries. For example, it is larger for Italy than Spain. Results in Table 19, although not conclusive as we acknowledge that this aspect of our paper needs further investigation, which we leave for future research, point in the direction that the different lockdown measures across European countries have influenced firms’ decisions to draw down credit lines. Therefore, although the “panic borrowing” has the same origin across Europe (i.e. lockdown policies), it impacted firms’ decisions to draw down credit lines differently.¹⁶ These results have important policy implications given that social distancing policies can generate negative externalities for firms and unexpectedly fly to liquidity.¹⁷

¹⁶We have also considered different quarters in our analysis. results are available upon request

¹⁷Credit line drawdowns also have serious implications for banks’ liquidity management since banks commit them. Firms, as we showed, rely on them as insurance, especially in bad states. Our results suggest that country flexibility is important, although more work is necessary on this.

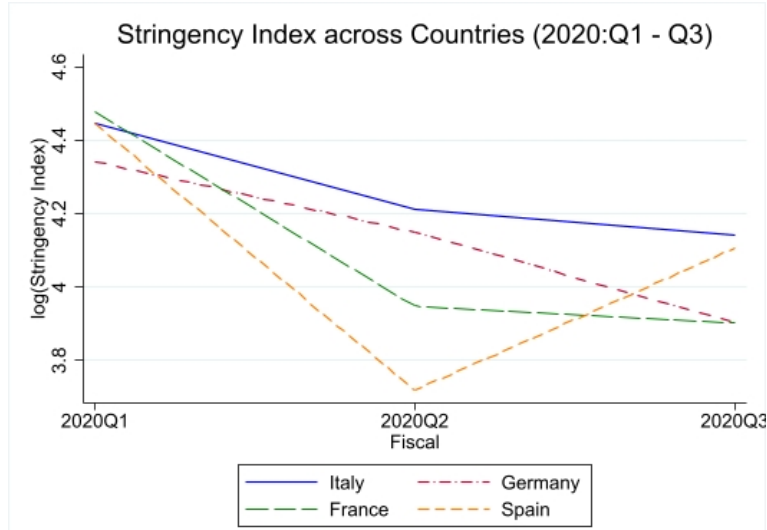


Figure 9. This diagram shows the strictness of lockdown policy across main European countries. The horizontal axis shows the three quarters when the COVID-19 pandemic burst. The vertical axis shows the logarithm of the Stringency Index which measures the strictness of ‘lockdown style’ policies.

| | Drawdown Size | | | | Credit Line Usage | | | |
|-------------------------|---------------------|-------------------|-------------------|--------------------|--------------------|--------------------|--------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| log(Stringency) | 0.023 (0.019) | 0.037* (0.019) | 0.034* (0.019) | 0.038** (0.019) | 0.126** (0.061) | 0.130** (0.061) | 0.151** (0.060) | 0.161*** (0.060) |
| log(Stringency)×Italy | 0.018*** (0.006) | | | | 0.045** (0.020) | | | |
| log(Stringency)×Germany | 0.000 (0.004) | | | | 0.030** (0.013) | | | |
| log(Stringency)×France | 0.014** (0.006) | | | | 0.041** (0.019) | | | |
| log(Stringency)×Spain | 0.012** (0.006) | | | | 0.014 (0.020) | | | |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 211 | 211 | 211 | 211 | 206 | 206 | 206 | 206 |
| R^2 | 0.140 | 0.101 | 0.125 | 0.120 | 0.134 | 0.133 | 0.131 | 0.112 |

Table 17. The impact of COVID-19 on Credit Line Drawdowns (Countries). This table shows the regression results of Eq. (9). The dependent variable is $Drawdown_{i,t}$ which contains either credit line drawdowns to total assets or the utilization of credit lines. $\log(Stringency)$ is the logarithm of the Stringency Index which records the strictness of ‘lockdown policies’ (Ritchie et al. 2020). $Country_i$ is a set of dummies indicating European countries such as Italy, Germany, France, and Spain. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of price-to-book ratio. Industry fixed effect is included. We report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Industrial Exposure to COVID-19 and Credit Lines Drawdowns

We showed that the economic shutdown of a large part of European economies following the COVID-19 shock led to a “panic borrowing” and cash accumulation. We also showed that this was driven by an unexpected shortfall in firms’ revenue, which differed across countries. We name work flexibility as the capacity to perform a job from home. Thus, results in the next sections, complement

and extend the ones reported earlier. [Bosshardt & Kakhbod \(2020\)](#) showed that the economic shutdown motivated firms to draw down their credit lines for a precautionary reasons but that firms less exposed to the COVID-19 shock used, in part, some of the cash from drawdowns to support investments. Differently from [Bosshardt & Kakhbod \(2020\)](#), we study the impact of the COVID-19 shock across industries based on their ability to perform jobs remotely (work flexibility). The idiosyncratic effect of COVID-19 across different industries is crucial as it helps to inform policymakers about policy responses to help the economy. As far as we know, this is the first paper to investigate this issue and directly link firms’ idiosyncratic risk (i.e. work and country flexibility), credit lines drawdowns and corporate liquidity management.

To define work flexibility, in this section, we follow the survey developed by [Dingel & Neiman \(2020\)](#) conducted on a range of 1,000 occupations in the United States, investigating how many can be conducted from home. The finding highlights the impact of “social distancing” on the risk of exposure to COVID-19 across industries. According to this finding, constructing a 2-digit sector classification code provides a benchmark to identify the relative ability of labour to carry out their occupational commitments across industries. For instance, for professionals, scientific, and technical services, the estimated impact is 0.8, indicating that most occupations under this classification are relatively less affected by the social distancing policy. In contrast, accommodation and food services are more affected, with the estimated exposure equal to 0.04. We define the weight of jobs that can be done from home by:

$$Exposure = 1 - Job\ Done\ at\ Home$$

where *Exposure* shows the effect of the pandemic on an industry as expressed by the labour drivers. A higher exposure value implies a lower ability of occupational capacities to be fulfilled while impacted by the pandemic. As *Job Done at Home* is within an interval between 0 and 1, *Exposure* is also located in the same range.

While the framework developed by [Dingel & Neiman \(2020\)](#) uses the North American Industry Classification System (NAICS), in our study, we follow the Bloomberg Industry Classification Standard (BICS). These two systems overlap in certain occupational types with specific disparities. For example, sectors are divided into unequal divisions,¹⁸ and the definition of level-2 sub-sector remains generic. We develop a detailed matching across the two systems by exploiting the classification information provided by each benchmark at level-3 industry groups and level-4 industries. Table (18) shows the industrial exposure to COVID-19 within two industrial levels. In Figure (10), we show firms’ access to their credit lines between 2020Q1 and 2020Q2. Energy, Technology, Real Estate and Materials are the ones that withdrew their credit lines during the pandemic shock.

The upper panel of Table (18) shows the main sectors of the industries. Consider Industrials (0.651) as an example. This contains not only Industrial Intermediate Products (0.78) but also Industrial Support Services (0.2). However, all the industries have more than half of the jobs affected by the pandemic, except Communications. If we define the sector which scores larger than 0.7 as an *exposed* one, then Materials, Health Care, Consumer Discretionary, and Energy are *exposed* sectors. On the contrary, sectors which scores less than 0.3 are *unexposed* ones. Communications is the only *unexposed* sector. Using the same approach to the level-3 industry groups in the lower panel of Table (18), there are 35 *exposed* and 10 *unexposed* industry groups in total. *Exposed* groups

¹⁸The number of level-1 or 2-digit sectors in the NAICS is 20, while the number in the BICS is merely 13.

| Panel A: Level-1 BICS Sectors | | | |
|---------------------------------------|----------|---------------------------------------|----------|
| Sector | Exposure | Sector | Exposure |
| Materials | 0.772 | Consumer Staples | 0.685 |
| Health Care | 0.771 | Industrials | 0.651 |
| Consumer Discretionary | 0.720 | Utilities | 0.630 |
| Energy | 0.710 | Real Estate | 0.580 |
| Technology | 0.697 | Communications | 0.272 |
| Panel B: Level-3 BICS Industry Groups | | | |
| Industry | Exposure | Industry | Exposure |
| Retail-Consumer Staples | 0.86 | Tobacco & Cannabis | 0.78 |
| Retail-Discretionary | 0.86 | Health Care Facilities & Services | 0.75 |
| E-Commerce Discretionary | 0.86 | Oil & Gas Services & Equipment | 0.75 |
| Engineering & Construction | 0.81 | Oil & Gas Producers | 0.75 |
| Transportation & Logistics | 0.81 | Construction Materials | 0.75 |
| Home Construction | 0.81 | Metals & Mining | 0.75 |
| Software | 0.78 | Leisure Facilities & Services | 0.7 |
| Transportation Equipment | 0.78 | Gas & Water Utilities | 0.63 |
| Machinery | 0.78 | Electric Utilities | 0.63 |
| Aerospace & Defense | 0.78 | Renewable Energy | 0.63 |
| Chemicals | 0.78 | Electricity & Gas Marketing & Trading | 0.63 |
| Electrical Equipment | 0.78 | Real Estate Owners & Developers | 0.58 |
| Beverages | 0.78 | REIT | 0.58 |
| Technology Hardware | 0.78 | Real Estate Services | 0.58 |
| Steel | 0.78 | Food | 0.48 |
| Medical Equipment & Devices | 0.78 | Wholesale-Discretionary | 0.48 |
| Containers & Packaging | 0.78 | Wholesale-Consumer Staples | 0.48 |
| Apparel & Textile Products | 0.78 | Publishing & Broadcasting | 0.28 |
| Biotech & Pharma | 0.78 | Cable & Satellite | 0.28 |
| Industrial Intermediate Products | 0.78 | Internet Media & Services | 0.28 |
| Diversified Industrials | 0.78 | Technology Services | 0.28 |
| Home & Office Products | 0.78 | Telecommunications | 0.28 |
| Forestry, Paper & Wood Products | 0.78 | Entertainment Content | 0.28 |
| Semiconductors | 0.78 | Industrial Support Services | 0.2 |
| Automotive | 0.78 | Commercial Support Services | 0.2 |
| Household Products | 0.78 | Advertising & Marketing | 0.2 |
| Leisure Products | 0.78 | Consumer Services | 0.2 |
| Construction Materials | 0.78 | | |

Table 18. **Industrial Exposure to the COVID-19 Shock.** This table shows the pandemic exposure across industries. The upper panel displays the exposure across Level-1 BICS sectors. The lower panel displays the exposure across Level-3 BISC industry groups.

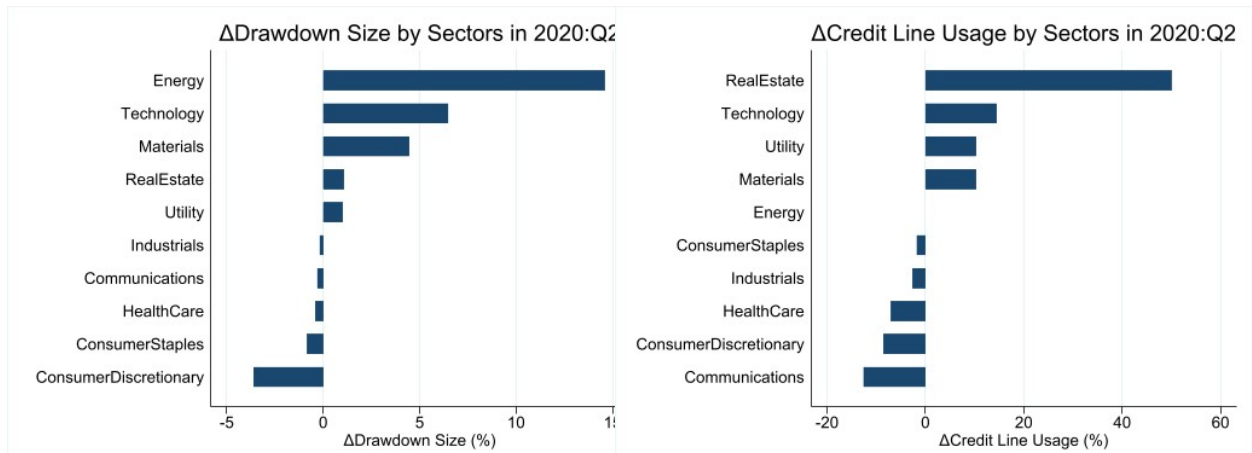


Figure 10. The diagram on the left shows the absolute difference in drawdowns between 2020:Q1-Q2 as a percentage of firms' total assets, whilst the diagram on the right shows firms' credit line utilization difference over the same time period, as a percentage of the firms' total assets.

including Retail-Consumer Staples, Retail-Discretionary, E-Commerce Discretionary, Engineering & Construction, Transportation & Logistics, Home Construction, Software, Transportation Equipment, Machinery, Aerospace & Defence, Chemicals, Electrical Equipment, Beverages, Technology Hardware, Steel, Medical Equipment & Devices, Containers & Packaging, Apparel & Textile Products, Biotech & Pharma, Industrial Intermediate Products, Diversified Industrials, Home & Office Products, Forestry, Paper & Wood Products, Semiconductors, Automotive, Household Products, Leisure Products, Construction Materials, Tobacco & Cannabis, Health Care Facilities & Services, Oil & Gas Services & Equipment, Oil & Gas Producers, Construction Materials, Metals & Mining, Leisure Facilities & Services. *Unexposed* groups consist of Publishing & Broadcasting, Cable & Satellite, Internet Media & Services, Technology Services, Telecommunications, Entertainment Content, Industrial Support Services, Commercial Support Services, Advertising & Marketing, Consumer Services.¹⁹

5.1 Work Flexibility and Credit Lines Drawdowns

5.1.1 Industry Groups

We divide the level-1 sectors into three groups: *Exposed*, *Unexposed*, and *Mild*. *Exposed* is the sector with a score higher than 0.75. *Unexposed* stands for the sector with a score lower than 0.3. *Mild* is the sector with a score between 0.3 and 0.75. Thus, the proportions of *Exposed*, *Unexposed*, and *Mild* are 64.6%, 18.2%, and 17.2%, respectively. It suggests that more than half of the firms are exposed to the pandemic. Less than one-fifth of the firms could *survive* the pandemic and the corresponding social distancing policy.

Based on these three industry groups, we estimate the effect of social distancing on firms' credit line drawdowns, investment and cash holdings. We construct an industry fixed effect panel regression model, removing the time effect. We use the following specification:

$$Y_i = \alpha + \beta_1(\text{Industry Groups}_i \times 2020:Q2) + \gamma X_i + \epsilon_i \quad (10)$$

The dependent variable, Y_i , consists of: 1) Credit line usage, equal to the drawn amount relative to the total committed amount of credit lines; 2) Investment, equal to capital expenditure scaled by non-cash assets; and 3) Cash holdings, equal to cash scaled by non-cash assets. The *Industry Groups*_{*i*} is, *Exposed*, *Unexposed*, and *Mild*, respectively. *2020:Q2* is a dummy equal to 1 indicating the time of the shock. X_i is a set of control variables like the ones in the previous sections. The interaction coefficient shows how the specific industry group performs during the shock period.

Table (19) shows the results. During the pandemic shock, only firms less exposed to the pandemic shock reduced credit lines (Panel A). The remaining firms used more of their credit lines than they usually did. All the firms reduced investments. In Panel B, we can see that the coefficients of the interactions are negative, and only the one for the group *Mild* × *2020:Q2* is significant. If we consider cash holdings, both *Unexposed* and *Mild* increase the size of cash. The coefficient of the interaction *Exposed* × *2020:Q2* is negative but insignificant.

In a nutshell, there is evidence that European firms used their credit lines for precautionary reasons and not for investment. Panel A in Table (19) shows that over 80% of firms affected by

¹⁹Note that table (18) does not contain all the sectors or industries within the BICS. It merely displays the sectors or industry groups of our sampling firms.

the pandemic, to some extent, drew down their credit lines in anticipation of a liquidity shock. Figure (11) shows that particularly firms within the group mild are the firms with the worst EBITDA position among the three groups. These results are in line with what was already discussed earlier. At the start of the pandemic shock, firms affected by the lockdown (less work flexibility) saw a significant drop in their expected revenue. They responded by drawing down their credit lines and accumulating cash. These and previous also results suggest a novel interplay between social distancing policies (work flexibility and, in part, country flexibility), credit lines drawdowns and liquidity management as a new mechanism of firms' financial constraints.

| | (1) | (2) | (3) |
|--|-------------------|----------------------|----------------------|
| Panel A: Credit Line Usage | | | |
| Exposed×2020:Q2 | 0.091* (0.047) | | |
| Unexposed×2020:Q2 | | -0.225*** (0.075) | |
| Mild×2020:Q2 | | | 0.165** (0.078) |
| Controls | yes | yes | yes |
| Industry FE | yes | yes | yes |
| Observations | 800 | 800 | 800 |
| Adjusted R^2 | 0.037 | 0.067 | 0.040 |
| Panel B: Investment (Capex-to-non-cash Assets) | | | |
| Exposed×2020:Q2 | -0.003 (0.002) | | |
| Unexposed×2020:Q2 | | -0.002 (0.003) | |
| Mild×2020:Q2 | | | -0.007*** (0.003) |
| Controls | yes | yes | yes |
| Industry FE | yes | yes | yes |
| Observations | 917 | 917 | 917 |
| Adjusted R^2 | 0.122 | 0.120 | 0.127 |
| Panel C: Cash Holdings (Cash-to-non-cash Assets) | | | |
| Exposed×2020:Q2 | -0.012 (0.013) | | |
| Unexposed×2020:Q2 | | 0.048** (0.021) | |
| Mild×2020:Q2 | | | 0.036* (0.020) |
| Controls | yes | yes | yes |
| Industry FE | yes | yes | yes |
| Observations | 1100 | 1100 | 1100 |
| Adjusted R^2 | 0.443 | 0.441 | 0.437 |

Table 19. **Regression Result: Industrial Exposure to COVID-19 (Euro Area)**. The dependent variables are credit line usage in Panel A, capital expenditure scaled by non-cash assets in Panel B, and cash holdings scaled by non-cash assets in Panel C. The independent variables contain three dummies: *Exposed*, *Unexposed*, and *Mild*. *Exposed* is the sector with a score higher than 0.75. *Unexposed* stands for the sector with a score lower than 0.3. *Mild* is the sector with a score between 0.3 and 0.75. Controls are defined in the previous sections. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

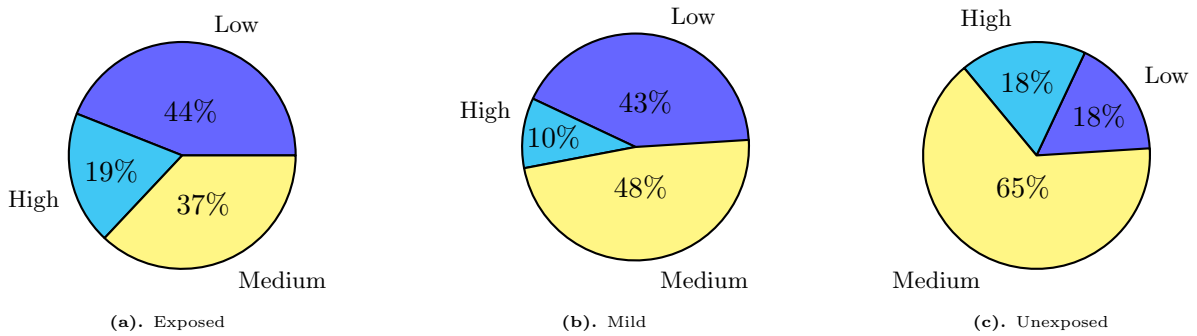


Figure 11. The diagram shows the EBITDA by different exposure levels in 2020:Q2. The left diagram reports the proportions of *Low*-, *Medium*- and *High*-EBITDA within the *Exposed* group. The middle diagram reports the proportion within the *Mild* group. The right diagram reports the proportion within the *Unexposed* group.

5.2 Social Distancing Policies, Work Flexibility and Corporate Draw-down Decisions

The previous results show a clear association between social distancing policies (work flexibility), firms' expected revenue, and panic borrowing. In this section, we extend the previous econometric setting and test the hypothesis that the inelastic nature of labour (less work flexibility) following the lockdown led to a sharp fall in revenue, especially in those industries more exposed to the pandemic shock. We introduce an indicator function:

$$I(Exposure) = \begin{cases} 1 & \text{if } Exposure \geq 0.75 \\ 0 & \text{if } Exposure \leq 0.3 \end{cases}. \quad (11)$$

This indicator captures two types of firms based on their risk exposure to the COVID-19 shock. To simplify, we only consider two groups: *Exposed* and *Unexposed* firms. As discussed earlier, we have also implemented a two-stage least-squares (2SLS) to account for possible endogeneity. The specification is as follows:

$$EBITDA_{i,t} = \delta_0 + \delta_1 I(Exposure) + \eta_{i,t} \quad (12)$$

$$Drawdown_{i,t} = \beta_0 + \beta_1 \widehat{EBITDA}_{i,t} + \beta_2 \widehat{EBITDA}_{i,t} \times 2020:Q2 + \gamma X_{i,t} + \epsilon_{i,t}. \quad (13)$$

The first-stage regression in equation (12) relates EBITDA with the inelastic nature of labour in those firms more exposed to social distancing policies (less work flexibility). The second-stage regression in equation (13) shows how EBITDA affects drawdown decisions. $\widehat{EBITDA}_{i,t}$ denotes the fitted value of *EBITDA* from the first-stage regression.

Table (20) shows the results. Columns (1) across (3) show the OLS regression within three subsamples: (1) both *Exposed* and *Unexposed* firms, (2) *Exposed* firms, and (3) *Unexposed* ones. Exposed firms carry the most sizeable beta coefficient with the expected sign: a negative shock on EBITDA is associated with increased credit line draw-downs. As robustness, we also designed a regression with three-way interaction. Column (4) shows the results. The coefficient of the three-way interaction is significant, consistent with results in columns (1) to (3).

Finally, column (5) in Table (20) shows the results from our 2SLS. The coefficient on the

interaction ($\widehat{EBITDA}_{i,t} \times 2020:Q2$) is significant at 10% level, confirming that the inelasticity of labour (less work flexibility) is important to understand firms' decisions to draw down credit lines. In a nutshell, work flexibility does help to understand the panic borrowing across European firms during the COVID-19 shock which led to credit lines drawdowns and cash accumulation.

| Dependent Variable: | Drawdown Size | | | | |
|---|----------------------------|--------------------------------|----------------------------------|------------------------------------|-----------------------------|
| | (1) OLS Two Firms | (2) OLS Exposed Firms | (3) OLS Unexposed Firms | (4) OLS 3-Way Interaction | (5) 2SLS Two Firms |
| $EBITDA_{i,t}$ | -0.186 (0.138) | -0.091 (0.155) | -0.390 (0.406) | -0.532 (0.359) | -2.418*** (0.689) |
| $EBITDA_{i,t} \times 2020Q2$ | -1.212** (0.510) | -1.666*** (0.602) | -0.200 (0.869) | 0.266 (0.729) | -0.740* (0.436) |
| $I(\text{Exposure}_i)$ | | | | 0.028 (0.018) | |
| $EBITDA_{i,t} \times I(\text{Exposure}_i)$ | | | | 0.450 (0.377) | |
| $I(\text{Exposure}_i) \times 2020:Q2$ | | | | 0.027* (0.016) | |
| $I(\text{Exposure}_i) \times EBITDA_{i,t} \times 2020:Q2$ | | | | -1.968** (0.927) | |
| $\text{Leverage}_{i,t}$ | 0.083*** (0.024) | 0.108*** (0.031) | 0.079** (0.034) | 0.086*** (0.024) | 0.037 (0.024) |
| $\log(\text{Assets}_{i,t})$ | -0.005*** (0.002) | -0.003 (0.002) | -0.019*** (0.004) | -0.005*** (0.002) | -0.006*** (0.002) |
| $\text{Undrawn CL}_{i,t}$ | 0.366*** (0.035) | 0.417*** (0.043) | 0.245*** (0.051) | 0.371*** (0.035) | 0.367*** (0.033) |
| $\log(P/B_{i,t})$ | -0.007 (0.005) | -0.002 (0.006) | -0.008 (0.008) | -0.004 (0.005) | 0.025** (0.010) |
| Industry FE | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes |
| Observations | 663 | 527 | 136 | 663 | 698 |
| Adjusted R^2 | 0.189 | 0.201 | 0.234 | 0.198 | 0.179 |

Table 20. **Credit Lines Drawdowns and EBITDA during the COVID-19 crisis (OLS & 2SLS)**. This table shows the results from Equation (13) in OLS and 2SLS forms. The dependent variable is credit line drawdowns scaled by total assets. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the second quarter of 2020, and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 The 2008 Financial Crisis and The 2012 European Crisis

Is work flexibility unique to the COVID-19 crisis? We shall consider this important issue in the following sections. We start with the 2008 financial crisis and follow with the 2012 European crisis.

5.3.1 Work Flexibility During the 2008 Financial Crisis

Table (21) shows weak empirical evidence that the work flexibility during the financial crisis impacted firms' expected revenue in Europe and drove credit line drawdowns. In a nutshell, work flexibility was not an issue during the 2008 financial crisis. The next section extends this to consider the European crisis.

| Dependent Variable: | Drawdown Size | | | | |
|---|----------------------------|--------------------------------|----------------------------------|------------------------------------|-----------------------------|
| | (1) OLS Two Firms | (2) OLS Exposed Firms | (3) OLS Unexposed Firms | (4) OLS 3-Way Interaction | (5) 2SLS Two Firms |
| EBITDA _{<i>i,t</i>} | -0.281*** (0.107) | -0.217* (0.122) | -0.438 (0.274) | -0.159 (0.215) | 0.119 (0.346) |
| EBITDA _{<i>i,t</i>} × 2008:Q3 | 0.171 (0.464) | 0.171 (0.483) | 0.237 (1.617) | -0.599 (0.826) | -0.508 (0.407) |
| I(Exposure _{<i>i</i>}) | | | | 0.039** (0.016) | |
| EBITDA _{<i>i,t</i>} × I(Exposure _{<i>i</i>}) | | | | -0.056 (0.247) | |
| I(Exposure _{<i>i</i>}) × 2008:Q3 | | | | -0.013 (0.022) | |
| I(Exposure _{<i>i</i>}) × EBITDA _{<i>i,t</i>} × 2008:Q3 | | | | 0.790 (0.964) | |
| Leverage _{<i>i,t</i>} | 0.100*** (0.025) | 0.171*** (0.032) | 0.065 (0.067) | 0.117*** (0.027) | 0.117*** (0.023) |
| log(Assets _{<i>i,t</i>}) | 0.001 (0.002) | -0.000 (0.002) | -0.001 (0.006) | 0.001 (0.002) | 0.001 (0.002) |
| Undrawn CL _{<i>i,t</i>} | 0.110*** (0.032) | 0.080** (0.038) | 0.159** (0.075) | 0.152*** (0.032) | 0.171*** (0.031) |
| log(P/B _{<i>i,t</i>}) | -0.005 (0.005) | 0.002 (0.006) | -0.009 (0.012) | -0.008 (0.005) | -0.008 (0.006) |
| Industry FE | yes | yes | yes | yes | yes |
| Times FE | yes | yes | yes | yes | yes |
| Observations | 634 | 520 | 114 | 634 | 692 |
| Adjusted R ² | 0.123 | 0.110 | 0.158 | 0.111 | 0.095 |

Table 21. **Credit Lines Drawdowns and EBITDA during the 2008 financial crisis (OLS & 2SLS)**. This table shows the estimations of Equation (13) in OLS and 2SLS forms. The dependent variable is credit line drawdowns scaled by total assets. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the third quarter of 2008 (the Collaps of Lehman Brothers), and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Work Flexibility and the 2012 European Crisis

Table (22) shows the empirical results. Work flexibility was not associated with corporate decisions to draw down credit lines during the 2012 European crisis. In sum, the “panic borrowing” observed during the COVID-19 shock amongst European firms is unique to that crisis. These and previous results are new and interesting as they point towards a story where the nature of shocks may matter to understand firms’ liquidity risk management. We are unaware of empirical papers investigating and discussing this important and new issue.

| Dependent Variable: | Drawdown Size | | | | |
|---|----------------------------|--------------------------------|----------------------------------|------------------------------------|-----------------------------|
| | (1) OLS Two Firms | (2) OLS Exposed Firms | (3) OLS Unexposed Firms | (4) OLS 3-Way Interaction | (5) 2SLS Two Firms |
| EBITDA _{<i>i,t</i>} | -0.081 (0.055) | -0.042 (0.058) | -0.123 (0.143) | -0.244** (0.103) | -0.222 (0.290) |
| EBITDA _{<i>i,t</i>} × 2012:Q3 | -0.128 (0.131) | -0.183 (0.123) | -0.342 (1.902) | -0.686 (1.036) | -0.411 (0.414) |
| I(Exposure _{<i>i</i>}) | | | | -0.001 (0.011) | |
| EBITDA _{<i>i,t</i>} × I(Exposure _{<i>i</i>}) | | | | 0.222* (0.120) | |
| I(Exposure _{<i>i</i>}) × 2012:Q3 | | | | -0.005 (0.011) | |
| I(Exposure _{<i>i</i>}) × EBITDA _{<i>i,t</i>} × 2012:Q3 | | | | 0.500 (1.045) | |
| Leverage _{<i>i,t</i>} | 0.084*** (0.018) | 0.053*** (0.018) | 0.303*** (0.060) | 0.087*** (0.018) | 0.056*** (0.018) |
| log(Assets _{<i>i,t</i>}) | -0.003*** (0.001) | -0.001 (0.001) | -0.019*** (0.004) | -0.003** (0.001) | 0.002 (0.002) |
| Undrawn CL _{<i>i,t</i>} | 0.455*** (0.033) | 0.370*** (0.035) | 0.726*** (0.088) | 0.465*** (0.032) | -0.001 (0.002) |
| log(P/B _{<i>i,t</i>}) | 0.002 (0.003) | 0.000 (0.003) | -0.000 (0.010) | 0.002 (0.003) | 0.011*** (0.003) |
| Industry FE | yes | yes | yes | yes | yes |
| Times FE | yes | yes | yes | yes | yes |
| Observations | 1054 | 889 | 165 | 1054 | 1149 |
| Adjusted R ² | 0.199 | 0.156 | 0.365 | 0.194 | 0.015 |

Table 22. **Credit Lines Drawdowns and EBITDA during the 2012 European crisis (OLS & 2SLS)**. This table shows the estimations of Equation (13) in OLS and 2SLS forms. The dependent variable is credit line drawdowns scaled by total assets. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the third quarter of 2012 (the launch of monetary policies), and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusion

Why did European firms draw down credit lines and accumulated cash during the COVID-19 shock? We studied this important issue in this paper. We showed that European firms went into a "panic borrowing" and that it was driven by an unexpected shortfall in revenue following the implementation of social distancing rules (and virus spread) across Europe. We also showed that firms with less work flexibility (or in countries with higher COVID cases) responded by dashing for cash. We showed that, in general, these firms had good solvency and liquidity positions. While these results are consistent with some theoretical models, see [Acharya et al. \(2012\)](#), they also open up to challenges for the same models as they assume credit lines exogenous. That is, credit lines are means to support investment decisions not to accumulate cash. The panic reported in this paper suggests that firms used credit lines for liquidity accumulation during the COVID-19 shock. We empirically implement a battery of econometric methodologies and quasi-natural experiments to investigate this issue the mechanism behind this. Finally, we showed a novel and exciting interplay mechanism between firms' work flexibility (somehow also country flexibility), idiosyncratic risk and credit lines drawdowns leading to cash accumulation. Our results raise new questions for banks and governments. The pandemic shock introduced a new and significant source of firms' idiosyncratic risk, social distancing and work flexibility. Banks cannot ignore it when managing their loans' portfolio. Also, our results make clear that a run on banks' credit lines can occur, and it depends on the nature of the aggregate risk (financial crisis vs COVID-19 shocks or others) and, probably, how this risk correlates with firms' idiosyncratic risk. These are important and new topics for theoretical and empirical research which we leave for further research. Finally, our results also have implications for European governments when designing future lockdown policies. They suggest that clear and effective communication as well as considering work flexibility, are essential to smooth the impact of aggregate shocks and the negative externalities for society from rum on banks' credit lines.

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Appendices

A Capex on Drawdowns

| | OLS | | IV | | | |
|---|----------------------|----------------------|-------------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | Undrawn Capacity (3) | Cash Holdings (4) | (5) | (6) |
| A. Regression results (using lagged variables) | | | | | | |
| Drawdown Size _{t-1} | -0.016*** (0.006) | -0.017*** (0.006) | -0.045*** (0.015) | -0.046*** (0.016) | -0.091*** (0.031) | -0.085*** (0.032) |
| Drawdown Size _{t-1} × 2020:Q2 | | 0.008 (0.021) | | 0.011 (0.033) | | -0.026 (0.038) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 366 | 366 | 293 | 293 | 389 | 389 |
| R ² | 0.233 | 0.233 | 0.225 | 0.226 | 0.221 | 0.222 |
| B. Regression results (using contemporaneous variables) | | | | | | |
| Drawdown Size _t | -0.015*** (0.004) | -0.016*** (0.004) | -0.048*** (0.013) | -0.048*** (0.014) | -0.141*** (0.037) | -0.136*** (0.038) |
| Drawdown Size _t × 2020:Q2 | | 0.003 (0.010) | | 0.001 (0.029) | | -0.020 (0.042) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 707 | 707 | 364 | 364 | 486 | 486 |
| R ² | 0.192 | 0.192 | 0.241 | 0.241 | 0.240 | 0.240 |

Table A1. **Capital Expenditure on Drawdowns (Euro Area)**. The table provides estimation results for lagged and contemporaneous specifications on the top and bottom panels, respectively. The dependent variable is capital expenditure scaled by total assets. The independent variables are drawdowns scaled by total assets and a time dummy indicating the second quarter of 2020. Columns (1) and (2) show the effect of the drawdowns on capital expenditures as a measure of investment decisions based on a benchmark estimation, whereas columns (3) across (6) show the corresponding impacts, based on two instruments, undrawn capacity and cash holdings in the previous period, respectively, to address the underlying endogeneity amongst drawdowns and investment decisions. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Cash Holdings

| | OLS | | IV | | | |
|---|---------------------|---------------------|--------------------|--------------------|---------------------|---------------------|
| | (1) | (2) | Undrawn Capacity | | Cash Holdings | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| A. Regression results (using lagged variables) | | | | | | |
| Drawdown Size_{t-1} | 0.116*** (0.039) | 0.116*** (0.041) | 0.264** (0.107) | 0.279** (0.113) | 2.991*** (0.163) | 3.005*** (0.170) |
| Drawdown $\text{Size}_{t-1} \times 2020:\text{Q2}$ | | -0.001 (0.133) | | -0.109 (0.246) | | -0.057 (0.194) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 391 | 391 | 313 | 313 | 430 | 430 |
| R^2 | 0.361 | 0.361 | 0.355 | 0.355 | 0.624 | 0.624 |
| B. Regression results (using contemporaneous variables) | | | | | | |
| Drawdown Size_t | -0.009 (0.025) | -0.004 (0.027) | 0.196** (0.081) | 0.205** (0.089) | 4.384*** (0.143) | 4.415*** (0.147) |
| Drawdown $\text{Size}_t \times 2020:\text{Q2}$ | | -0.038 (0.069) | | -0.050 (0.186) | | -0.149 (0.161) |
| Controls | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Observations | 816 | 816 | 389 | 389 | 536 | 536 |
| R^2 | 0.321 | 0.321 | 0.365 | 0.365 | 0.763 | 0.763 |

Table B1. **Cash Holdings on Drawdowns (Euro Area)**. The table provides estimation results for lagged and contemporaneous specifications on the top and bottom panels, respectively. The dependent variable is cash and cash equivalents scaled by total assets. The independent variables are drawdowns scaled by total assets and a time dummy indicating the second quarter of 2020. Columns (1) and (2) show the effect of the drawdowns on cash holdings as a measure of precautionary motives based on a benchmark estimation, whereas columns (3) across (6) show the corresponding impacts, based on two instruments, undrawn capacity and cash holdings in the previous period, respectively, to address the underlying endogeneity amongst drawdowns and investment decisions. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C RID

| | Drawdown Size | | | | Credit Line Usage | | | |
|---------------------------------|---------------------|----------------------|---------------------|---------------------|---------------------|--------------------|---------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Different Time Dummies | | | | | | | | |
| RID _{t-1} | 0.037*** (0.012) | 0.036*** (0.012) | 0.043*** (0.012) | 0.041*** (0.015) | 0.123** (0.049) | 0.117** (0.050) | 0.151*** (0.052) | 0.108* (0.063) |
| RID _{t-1} × 2020:Q1 | | 0.027 (0.040) | | | | 0.150 (0.163) | | |
| RID _{t-1} × 2020:Q2 | | | -0.048* (0.028) | | | | -0.196* (0.108) | |
| RID _{t-1} × 2020:Q3 | | | | -0.009 (0.021) | | | | 0.032 (0.088) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 388 | 388 | 388 | 388 | 381 | 381 | 381 | 381 |
| Adjusted R ² | 0.071 | 0.069 | 0.076 | 0.068 | 0.076 | 0.076 | 0.082 | 0.074 |
| Panel B: Different Firm Types | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Risk | Medium Risk | High Risk | All Firms | Low Risk | Medium Risk | High Risk |
| RID _{t-1} | 0.043*** (0.012) | 0.016 (0.017) | -0.079 (0.074) | -0.083 (0.132) | 0.151*** (0.052) | 0.125 (0.111) | -0.196 (0.231) | 0.185 (0.502) |
| RID _{t-1} × 2020:Q2 | -0.048* (0.028) | -0.143*** (0.045) | 0.015 (0.152) | 0.071 (0.217) | -0.196* (0.108) | -0.569* (0.294) | 0.270 (0.473) | 0.286 (0.822) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 388 | 83 | 199 | 105 | 381 | 79 | 199 | 102 |
| Adjusted R ² | 0.076 | 0.109 | 0.026 | 0.187 | 0.082 | 0.017 | 0.102 | 0.236 |

Table C1. **Regression Result: RID Ratio on Drawdowns (Euro Area)**. The table provides the baseline models with various interactions and within different sub-samples. In columns (1) through (4), the dependent variables are the ratio of drawdowns size (*Drawdowns/TA*). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A reports the baseline models given the interactions between the RID ratio and time dummies (*2020:Q1*, *2020:Q2*, and *2020:Q3*), respectively. Panel B reports the baseline models within the whole sample (*All Firms*) and three sub-samples (*Low-*, *Medium*, and *High-Risk*) based on firm types. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

| | Drawdown Size | | | | Credit Line Usage | | | |
|---------------------------------|----------------------|---------------------|-------------------|---------------------|---------------------|----------------------|--------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | All Firms | Low Distress | Medium Distress | High Distress | All Firms | Low Distress | Medium Distress | High Distress |
| Distress _t | 0.222*** (0.046) | 0.275** (0.125) | -0.069 (0.156) | 0.869*** (0.100) | 0.387*** (0.117) | 0.977*** (0.312) | -0.808* (0.416) | 1.049*** (0.282) |
| Distress _t × 2020:Q2 | -0.175*** (0.050) | -0.266** (0.127) | 0.186 (0.434) | 0.304 (0.235) | -0.276** (0.127) | -0.937*** (0.317) | 0.840 (1.155) | 0.683 (0.662) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes |
| Industry FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations | 804 | 239 | 418 | 146 | 788 | 231 | 413 | 143 |
| Adjusted R ² | 0.044 | 0.068 | 0.021 | 0.455 | 0.025 | 0.067 | 0.028 | 0.192 |

Table C2. **Drawdowns on Financial Distress by Firm Types.** The table provides the baseline regressions of credit line drawdowns on the financial distress by different firm types. In columns (1) through (4), the dependent variables are the ratio of drawdown size (*Drawdowns/Non-Cash Assets*). In columns (5) through (8), the dependent variables are the usage of credit lines. The independent variables are the distress and the interaction between the distress and the 2020:Q2 dummy. Apart from the regression on the whole sample (columns (1) and (5)), the regressions are also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Alternative Regression Discontinuity Design

We also use a different econometric setting following [Malenko & Shen \(2016\)](#), to investigate if shocks on firms' earnings drive firms' decisions to draw down credit lines:

$$\begin{aligned}
Drawdown_{i,t} = & \beta_0 + \beta_1 EBITDA_{i,t} + \beta_2 BelowCutoff_{i,t} + \beta_3 EBITDA_{i,t} \times 2020:Q2 \\
& + \beta_4 BelowCutoff_{i,t} \times 2020:Q2 + \beta_5 BelowCutoff_{i,t} \times EBITDA_{i,t} \\
& + \beta_6 BelowCutoff_{i,t} \times EBITDA_{i,t} \times 2020:Q2 + \gamma X_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{14}$$

where

$$BelowCutoff_t = \begin{cases} 1 & \text{if } Free\ Cash\ Flow_t \in [-\lambda, 0) \\ 0 & \text{if } Free\ Cash\ Flow_t \in [0, \lambda] \end{cases} \tag{15}$$

where λ denotes the bandwidth which is equal to half standard deviation of *Free Cash Flow_t* ($\lambda = 0.5\sigma$). Following [Malenko & Shen \(2016\)](#), we define an indicator variable *BelowCutoff* equal to one if the free cash flow is below 0 but considered within the bandwidth, and zero otherwise.

The main parameter of interest is β_6 which we expect to be negative and statistically significant, indicating that shocks on EBITDA explain the decisions of a group of firms (i.e. the ones whose EBITDA falls within the range) to draw down credit lines.

Regardless of the inclusion of a fixed effect in the model, there is robust evidence that firms' credit line drawdowns to total assets ratios increased during the pandemic. Figure (12) shows the individual drawdown effects based on equation (7) where the horizontal axis shows the bandwidth selections versus credit lines drawdowns in percentage points on the vertical axis and their associated 95% confidence intervals. Given the narrowest bandwidth choice of $\pm 0.5\sigma$ surrounding the threshold, drawdown decisions are strikingly different, with the difference remaining statistically significant and retaining its economic size under alternative scenarios. Figure (13) shows the same effect based on the results in Table (D3).

| Dependent Variable: | Drawdown Size | | | | | | | |
|--|-----------------------|----------------------|------------------------|----------------------|----------------------|----------------------|------------------------|----------------------|
| | $\lambda = 0.5\sigma$ | | $\lambda = 0.75\sigma$ | | $\lambda = \sigma$ | | $\lambda = 1.25\sigma$ | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| EBITDA _{<i>i,t</i>} | -0.991*** (0.318) | -0.948*** (0.322) | -0.848*** (0.272) | -0.808*** (0.276) | -0.895*** (0.242) | -0.824*** (0.246) | -0.822*** (0.239) | -0.744*** (0.243) |
| BelowCutoff _{<i>i,t</i>} | -0.037** (0.015) | -0.037** (0.016) | -0.019 (0.014) | -0.018 (0.014) | -0.017 (0.012) | -0.017 (0.013) | -0.014 (0.012) | -0.013 (0.012) |
| EBITDA _{<i>i,t</i>} × 2020:Q2 | 0.428 (0.706) | 0.475 (0.707) | -0.105 (0.592) | -0.071 (0.592) | -0.292 (0.494) | -0.266 (0.492) | -0.355 (0.500) | -0.343 (0.498) |
| BelowCutoff _{<i>i,t</i>} × 2020:Q2 | 0.059** (0.025) | 0.065*** (0.025) | 0.040* (0.021) | 0.043** (0.021) | 0.038* (0.020) | 0.041** (0.021) | 0.031 (0.020) | 0.034* (0.020) |
| BelowCutoff _{<i>i,t</i>} × EBITDA _{<i>i,t</i>} | 0.906* (0.486) | 0.782 (0.493) | 0.600 (0.441) | 0.474 (0.447) | 0.640 (0.391) | 0.554 (0.395) | 0.575 (0.382) | 0.484 (0.386) |
| BelowCutoff _{<i>i,t</i>} × EBITDA _{<i>i,t</i>} × 2020:Q2 | -3.262*** (1.169) | -3.349*** (1.185) | -2.564** (1.068) | -2.446** (1.069) | -2.412** (0.990) | -2.370** (0.988) | -2.287** (1.001) | -2.281** (0.998) |
| log(Assets _{<i>i,t</i>}) | -0.010*** (0.002) | -0.009*** (0.003) | -0.010*** (0.002) | -0.011*** (0.002) | -0.008*** (0.002) | -0.008*** (0.002) | -0.009*** (0.002) | -0.009*** (0.002) |
| Leverage _{<i>i,t</i>} | 0.068** (0.030) | 0.081** (0.032) | 0.066** (0.027) | 0.084*** (0.028) | 0.064*** (0.024) | 0.076*** (0.025) | 0.058** (0.024) | 0.067*** (0.024) |
| Undrawn CL _{<i>i,t</i>} | 0.321*** (0.048) | 0.336*** (0.049) | 0.256*** (0.043) | 0.268*** (0.044) | 0.263*** (0.039) | 0.280*** (0.040) | 0.237*** (0.037) | 0.253*** (0.037) |
| log(Price _{<i>i,t</i>}) | 0.009** (0.004) | 0.010** (0.005) | 0.005 (0.004) | 0.005 (0.004) | 0.003 (0.003) | 0.003 (0.004) | 0.004 (0.003) | 0.004 (0.003) |
| Fixed Effects | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 328 | 328 | 458 | 458 | 544 | 544 | 596 | 596 |
| Adjusted R ² | 0.240 | 0.247 | 0.159 | 0.170 | 0.151 | 0.162 | 0.130 | 0.142 |

Table D3. **Alternative Regression Discontinuity Design on Drawdowns.** This table shows an alternative regression discontinuity design of credit line drawdowns on the EBITDA. The dependent variable is *Drawdown Size*, indicating the credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, *BelowCutoff*, a dummy equal to one that the firms have performance just below the cutoff point, and zero the firms are just above the cutoff point, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included as indicated. Columns (1), (3), (5), (7), and (9) use subsamples based on the performance just below the threshold. The rest columns use subsamples based on the performance just above the threshold. σ denotes the standard deviation of the performance. A real number multiplying σ (for example, -0.5σ) represents the direction and distance away from the threshold. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

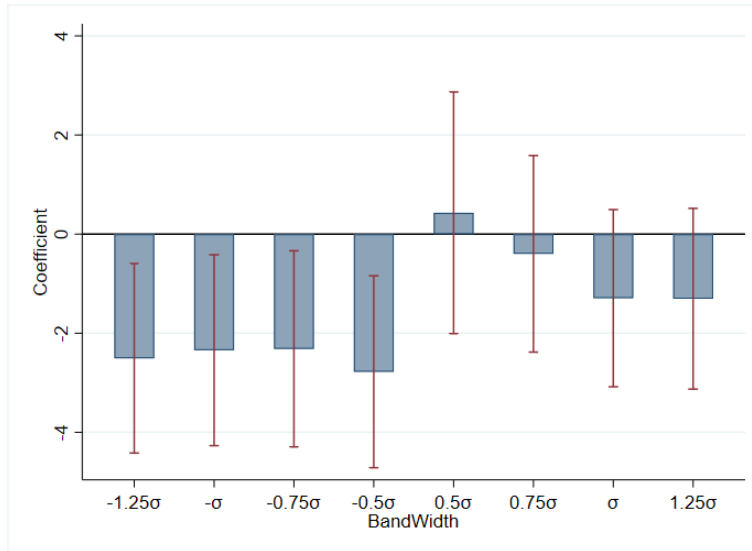


Figure 12. The diagram shows the estimated percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. The horizontal axis shows several bandwidth selections. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections considers even intervals around zero-earning outcomes and shows a sharp shift in the firms' behaviours to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.

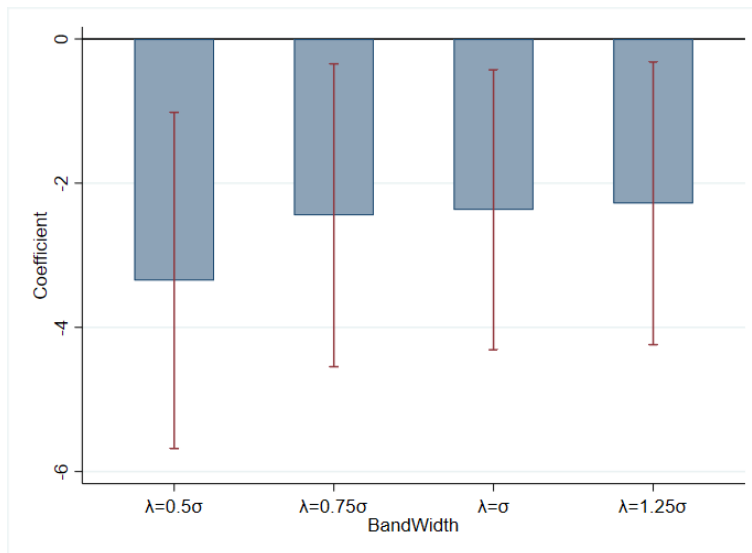


Figure 13. The diagram shows the estimated cross-sectional differential percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in draw down decisions across the pairwise above- versus below-threshold value. The horizontal axis shows several bandwidth selections proportional to the standard deviation of the empirical distribution summarising EBITDA observations. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections considers even intervals around zero-earnings and shows a sharp shift in the firms' behaviours to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.